

Evaluating Faulty State Occurrence in Wildfire UAS Missions Using Markov Chains

Sequoia R. Andrade^{*} and Seydou Mbaye[†]

Intelligent Systems Division, NASA Ames Research Center, Moffett Field, CA, 94035, USA

Misty D. Davies[‡]

Intelligent Systems Division, NASA Ames Research Center, Moffett Field, CA, 94035, USA

Garfield Jones[§]

Department of Industrial and Systems Engineering, Morgan State University, Baltimore, MD, 21251, USA

As autonomous technology advances, unmanned aircraft systems are increasingly integrated into emergency response missions, such as wildfire response. These systems must be safe with less risk than non-autonomous counterparts, yet quantifying the risk associated with present-day and future systems conventionally relies solely on expert opinion and little data. Instead, combining narrative mishap reports with probabilistic analysis can provide a method for evolutionary and timely risk analysis. In this paper, we present a framework for a data-driven probabilistic risk assessment style analysis, where hazard events and rates originate from documented UAS mishaps. The framework is applied to a UAS mapping mission in wildfire response, including a fault tree analysis, event tree analysis, and probabilistic analysis using Markov Chains. The analysis provides an enumeration of hazards in the system, hazard events that can lead to top events, the probability of experiencing a specific top event, and the expected time until a faulty state occurs in present-day operations.

I. Nomenclature

<i>ETA</i>	=	Event Tree Analysis
<i>FTA</i>	=	Fault Tree Analysis
<i>IASMS</i>	=	In-time Aviation Safety Management System
<i>MC</i>	=	Markov Chain
<i>PRA</i>	=	Probabilistic Risk Assessment
<i>SMS</i>	=	Safety Management System
<i>UAS</i>	=	Unmanned Aircraft System

II. Introduction

Unmanned aircraft systems (UAS) are increasingly deployed in disaster response, including hurricane relief and recovery, search and rescue, and wildfire suppression operations [1]. Wildfires especially employ UAS in a variety of mission operations, such as near real-time mapping, aerial ignitions, and swarms with connectivity boosters [2]. With climate change influencing the frequency and severity of wildfires [3], future response operations envision expanding the use of UAS with both larger fleets and increased autonomy.

Future operations with highly autonomous UASs must provide an equal to or lesser than risk than present day UAS operations in response to known hazards in the system. Hence, there is a need to explicitly quantify the likelihood of faulty states in existing UAS operations, as well as identify potential likelihood thresholds that enable an acceptable value

^{*}Research Engineer, HX5 LLC., AIAA Member, sequoia.r.andrade@nasa.gov, funded Under Prime Contract No. 80ARC020D0010 with the NASA Ames Research Center.

[†]Researcher, NASA Ames Research Center, AIAA Student Member, seydou.mbaye@nasa.gov

[‡]Associate Chief for Aeronautics Systems - Intelligent Systems (TI) Division, Airspace Operations and Safety Program (AOSP) Technical Advisor for Assurance and Safety, AIAA Fellow, misty.d.davies@nasa.gov.

[§]Assistant Professor, Industrial and Systems Engineering, Morgan State University, garfield.jones@morgan.edu.

or risk. Simultaneously, future operations require enhanced safety management through data-driven and continuous risk assessment methodologies [4–7]. To this end, we present a data-driven probabilistic risk assessment (PRA) style analysis of a UAS mapping mission in wildfire response, including hazard identification, event tree analysis, fault tree analysis, and Markov Chain analysis. Hazards and occurrence rates are extracted from the Department of the Interior and United States Forest Service hosted Aviation Safety Communiqué (SAFECOM) report repository, allowing for an assessment informed solely by documented hazards. In turn, this methodology can be applied in an iterative pipeline where risk assessment is continuously performed as new safety reports are documented.

Using safety reports for hazard identification provides real-world data-informed hazard occurrence rates. PRA is a well-established method used across safety critical applications, from nuclear power plant management [8, 9] to human space flight systems [10, 11], providing relevant insight on fault modes present in a system and potential causes. Markov Chain analysis is chosen for its ease of interpretation and ability to provide long run proportions of time in faulty states, probability of entering faulty states, and scalability [12, 13]. As a result, this research provides a method for detailed evaluation of faulty states with a case study on a UAS mission in wildfire response operations. The analysis provides an enumeration of hazards in the system, hazard events that can lead to top events, the probability of experiencing a specific top event, and the expected time until a faulty state occurs in present-day operations. These results are familiar components of conventional risk assessment performed in Safety Management Systems.

III. Background

A. Safety Management Systems

Safety Management Systems (SMSs) are present in numerous industries and play a core role in keeping the national airspace safe through the identification and management of risk across all operations, including aerial wildfire suppression missions and commercial flight. The Federal Aviation Administration (FAA) defines an SMS through Order 8000.369C as a formal and structured system integrating into all aspects of operations with specified procedures and policies [14]. In essence, the SMS provides a way to control hazards pertaining to a given operation in an effort to minimize incidents. This is accomplished through the four pillars of safety defined in an SMS in Figure 1: Safety Policy, Safety Risk Management, Safety Assurance, and Safety Promotion. The United States Forest Service (USFS) has its own guidance for aviation SMS in accordance with the FAA, which defines specific implementations of the four pillars [15]. For example, the USFS defines the Aviation Safety Communiqué (SAFECOM) reporting system within the Safety Assurance pillar as a mechanism for collecting mishap data and corrective actions [15]. While the SMS is effective for what it was designed for, it does not scale to the rapid transformation the National Airspace System has been undergoing, prompting calls for the development of a novel type of SMS that can adapt to the new entrants and operations, such as UAS in wildfire response [6]. Instead, a future In-Time Aviation SMS (IASMS) will need to continuously assess, monitor, and mitigate risk at scale by connecting the previously singular pillars [4, 5]. This research works towards integrating data from safety assurance activities directly into risk management by using mishap reports collected during operations for hazard identification and faulty state analysis of future missions, as seen in Figure 1. While using data for risk management is not a new concept, the idea of adjusting quantitative assessments continuously as new data arrives is a key component of the future IASMS. Hence, we work towards identifying appropriate scalable assessment methods that can be used directly on SMS artifacts, like safety reports.

B. Markov Chains in Probabilistic Risk Analysis

Probabilistic risk assessment (PRA) is a formal method for estimating the likelihood of hazardous and/or faulty events occurring during a system operation. The general steps of a PRA include hazard identification, fault tree modeling, event tree modeling, and Bayesian inference for probability estimation. Markov chains can play a key role in probability estimation through the Markov Chain Monte Carlo (MCMC) process [16], which can be used to provide insight on the distribution of a failure rates, as well as through direct modeling of system state transitions.

A Markov Chain (MC) is a probabilistic model describing a system’s movement between states defined by the probability of transitioning from one state to another state in the next time step. Hence, a MC with two states in the state space (e.g., nominal and faulty) is defined by a 2×2 probability transition matrix. The Markov Property dictates the probability of being in a certain state, x , at the next step, time $t + 1$, is only dependent on the current state, X_t :

$$P(X_{t+1} = x | X_t = x_t, X_{t-1} = x_{t-1}, \dots, X_0 = x_0) = P(X_{t+1} = x | X_t = x_t) \quad (1)$$

This modeling framework allows for the study of specific system characteristics, such as the long run proportion of

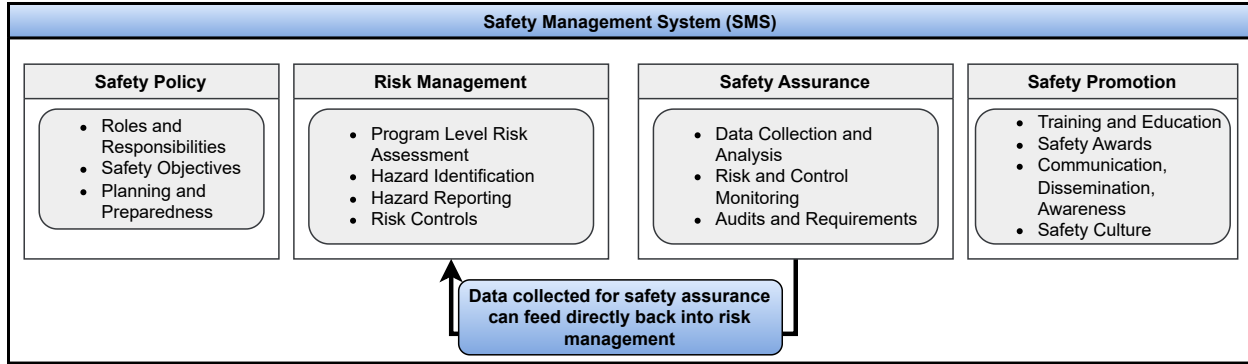


Fig. 1 The Traditional “Four Pillars” of a Safety Management System with emphasis on connecting Safety Assurance and Risk Management[14, 15]

time in each state and the probability of being a specified state given a starting state after t time steps. A special type of Markov chain relevant to failure analysis is the Poisson Process, where failures or hazards occur in a system according to a Poisson distribution with rate λ . Other variations of Markov Chains include the Renewal Process, Markov Decision Process, Hidden Markov Model, and Markov Chain Monte Carlo. Another use of Markov chains is in the estimation of stochastic differential equations, which has been applied to three-dimensional airspace conformance [17].

Markov chains have been applied to numerous systems to analyze risk and reliability, including novel unmanned aircraft demonstrators [18], carbon capture and storage systems [19], and automated docking space craft [20]. Markov chains have recently been applied to maritime accidents to determine long term risk through a probabilistic risk matrix [21]. In agreement with the existing applications of Markov chains for probabilistic risk analysis, this paper uses Markov Chains for analyzing unmanned aircraft failures during wildfire response operations.

C. Unmanned Aircraft Systems in Wildfire Response

Wildfire incidents have seen an increase in volume and complexity over the past few years in the United States [22]. As a result, wildfire management efforts, an already complicated task [23], have become more problematic [24], prompting calls for the inclusion of Unmanned Aircraft Systems in an effort to offload risks inherent to firefighters onto UAS. Previous studies have found that experts find UAS useful for various operations, including site survey, prevention, response, surveillance, search and rescue, and evacuation [25].

In wildfire response in particular, UAS are commonly used for both day time and night time fire infrared mapping, general surveillance, and aerial ignition operations [26, 27]. UAS types can range from very small nano aircraft for short surveillance missions, to large long-range aircraft for aerial ignition missions [27]. International projects, such as RESPONDRONE, aim to develop an integrated system to deploy and operate multiple UAS for data collection in early emergency response[28]. While UAS are currently used often for reconnaissance and fire mapping, novel UAS configurations have been proposed for swarm missions[26] and fire suppression missions [29]. Despite increasing deployment in wildfire response operations, UAS face shortcomings due to their battery lifespan, the harsh operational environment caused by fires, heterogeneous ground control systems, and need for specialized mission-specific payloads [27].

Several quantitative and qualitative methods have been used for risk assessment of UAS missions, including probabilistic Bayesian Belief Networks (BBN) [30], standard risk analysis methods, System-Theoretic Accident Model and Processes (STAMP) [31], Specific Operations Risk Assessment (SORA) [32], and Markov models [33]. Fault trees can be extended to BBNs, where causes, hazards, and top events are modeled in a probabilistic network to obtain a target level of safety and analyze the impact of potential mitigations [30]. While preliminary studies measure UAS failures in this manner, these studies use hypothetical failure rates and estimates from a wide variety of failure reports for a generic use case rather than utilizing operation-specific failure data for a situation-specific risk analysis [30]. In contrast, SORA provides a detailed assessment for each individual flight for specific missions; however, the method is time consuming and not well adapted to emergency response missions [32]. Other research has used Markov models with a backtracking process algorithm to identify sequences of events leading to undesired outcomes in UAS control systems [33].

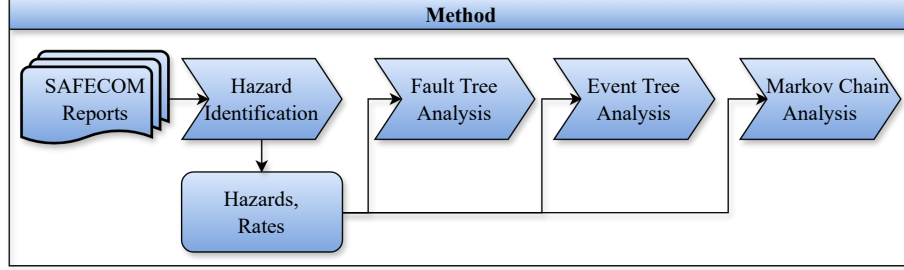


Fig. 2 Method flowchart showing the use of historical documents for hazard identification and further analyses.

IV. Methods

To evaluate faulty state occurrence in a wildfire surveillance UAS mission, we use a PRA-inspired analysis with steps displayed in Figure 2. First, hazards are identified from the SAFECOM database, which is a United States Forest Service and Department of the Interior co-hosted platform for documenting aircraft near-misses, mishaps, hazards, and accidents [34, 35]. Annual reports from the DOI and USFS are used to estimate annual failure rate per number of flights, resulting in a table of hazards and occurrence rates [36, 37]. Then the hazard list with failure rates is used to create a fault tree analysis, event tree analysis, and a Markov Chain analysis. The core methodology components are described in detail in the following subsections.

A. Hazard Identification

Hazard identification can be performed manually or via natural language processing techniques. For the scope of this research, reports are manually analyzed by two experts. First, the full data set is filtered down to only reports that are relevant for the specific mission profile (e.g., aerial mapping). For each report, an initiating event, high-level failure category, and resulting top event outcome are documented according to the following definitions:

- **Initiating Event:** a specific event during the flight that leads to a top event. For example, an engine failure or airspace conflict.
- **Failure Category:** a group of initiating events that fall under the same failure mode. For example, engine failures and propeller arm disconnections are both equipment failures.
- **Top Event:** a negative outcome of an initiating event, which may or may not occur after the event. For example, a result of loss of UAS after an engine fails and the UAS crashes.

During the hazard identification, we first read reports for initiating events and resulting top events, then group similar initiating events into failure categories. Breaking down hazards into initiating events, failure categories, and top events are useful for considering occurrence frequencies and rates of different levels of hazards. After reports are tagged accordingly, top event occurrence frequencies are calculated and failure rates for each year are estimated according to Equation (2), where F_t is the top event frequency for year t and N_t is the number of flights in year t .

$$R_t = \frac{F_t}{N_t} \quad (2)$$

B. Fault Tree Analysis

Fault tree analysis (FTA), a visual method helping visualize the chronological order of a system or subsystem failure, has been widely used since the early 1960s [38]. It is a top-down, widely used hazard analysis method that has seen application in various domains such as in aerospace [39]. Fault trees are built after the hazard identification step by tracing initiating events to failure categories and resulting top events. Note that due to the construction of the document labeling, a fault tree can be automatically generated via programming from a set of documents by building a tree from the relations.

C. Event Tree Analysis

Event tree analysis (ETA) is another type of graphical modeling for probabilistic risk assessment that begins by considering an initiating event, then tracing proceeding events to eventual system outcomes. ETA is often used in

conjunction with FTA and provides a detailed view of the sequence of events leading to a top event. Event trees are built from reports by selecting an initiating event and filtering the reports to fit that criteria. Then, each report is read and the possible events following the initiating event are noted. The resulting event tree is created from the complete set of paths possible from the reports, with probabilities assigned to each outcome based on the frequency in the reports.

D. Markov Chain Analysis

Finally, a Markov chain enabled analysis is performed using the failure rates and top events discovered during hazard identification. The Markov chain consists of a nominal state and an additional s states for the identified top events, resulting in an $s + 1$ state chain. To construct the chain, the probability of each faulty state occurring in the next time step is needed. Time to failure is conventionally modeled using an exponential distribution, with probability density function in Equation (3).

$$f(x, \lambda) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad (3)$$

Hence, the distribution of the time until a top event can be modeled by estimating the parameter of the exponential distribution, $\beta = \frac{1}{\lambda}$. For this research, the parameter β is estimated using the maximum likelihood estimator $\hat{\beta}$ in Equation (4), where β_i is the failure rate calculated for the i^{th} year.

$$\hat{\beta} = \sum_{i=1}^n \frac{\beta_i}{n} \quad (4)$$

A confidence interval for the parameter β is estimated using bootstrapping, which involves taking b new $\hat{\beta}$ estimates. For each new estimate, n samples are taken with replacement from the original n data points. Then, the b new estimates are ordered into a distribution and the lower and upper bounds for the 95% region are calculated.

The exponential distribution with the estimated parameter can then be used to calculate the probabilities of each faulty state occurring in the next time step by using the cumulative density function. Once the Markov chain is constructed, we then analyze properties of the chain to better understand faulty state occurrence, including the expected number of time steps, in this case flights, until a faulty state occurs. Since the chain construction creates nominal as a transient state and faults as absorbing states, the expected time in transient states is equivalent to the expected number of flights until a faulty state occurs. The expected time in transient states can be analytically solved. Given that P_t is the $m \times m$ portion of P for transitions between transient states, $s = 1, \dots, m$, then the expected total time in transient state s , $g(s)$, is given by Equation 5, where I_m is the $(m \times m)$ identity matrix.

$$\begin{bmatrix} g(1) \\ \vdots \\ g(m) \end{bmatrix} = [I_m - P_t]^{-1} \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \quad (5)$$

A confidence interval for the number of time steps until a faulty state is constructed by using the lower and upper bounds of the confidence interval on β to build lower and upper bound distributions, then constructing lower and upper bound Markov chains and repeating the process above.

V. Results

A. Hazard Identification

Since we are interested in aerial mapping missions during wildfire incidents, the SAFECOM data is filtered according to those parameters. The distribution of SAFECOM reports from general UAS missions, wildfire UAS missions, and wildfire UAS mapping missions is available in Figure 3. From Figure 3, we can see that mishap reports on wildfire UAS missions is increasing overtime, with a large proportion of these results from mapping operations. This resulted in a total of sixty-four mishap reports spanning from 2015-2022. Of the sixty-four reports, one was removed from the analysis because it was blank and two reports contained two failure modes each.

Each report narrative is examined and assigned one or more initiating events, associated high-level failure mode category, and associated top event or outcome. In turn, a list of twenty-two initiating events, four failure mode categories,

and two top events were identified from the report set. Lower level initiating events, enumerated in Table 1 are grouped into similar resulting failure mode categories defined in Table 3 and top events defined in Table 2. After getting the frequency of each top event per year, we estimate the failure rate per number of flights.

To estimate the failure rate, additional annual reports from the DOI and USFS are used to identify the number of UAS flights per year and the percentage of mapping flights. The data on mission distribution is limited for years 2015-2021, so 2022 is used to calculate the percentage of flights for wildfire mapping missions. In 2022, about 15% of flights were mapping missions and 42% were wildfire missions [36]. Using naive probability in Equation 6, we can estimate the percent of flights for wildfire mapping missions resulting in 6.3% of flights relevant to our case study.

$$P(\text{Wildfire \& Mapping}) = P(\text{Wildfire}) * P(\text{Mapping}) = 0.42 * 0.15 = 0.063 \quad (6)$$

We scale the annual total flights by this percentage to estimate the amount of flights during wildfire mapping missions, with the total flights and estimated wildfire mapping flights displayed in Figure 4. Together, Figure 3 and Figure 4 show that the number of UAS flights is increasing at faster rate than SAFECOM mishap reports, indicating mishaps are occurring less often in 2022 than in previous years, such as 2015 and 2016.

Failure rates for each top event are calculated using the estimated flights per year, with top event frequency and rate per year shown in Figure 5 and Figure 6 respectively. The number of events increases overtime, with the number of flights until an event decreasing over time in turn. The number of flights until a top event appears to stabilize from 2020-2022, while 2017-2019 have more variable failure rates. The variation in failure rate in turn impacts the range and accuracy of the Markov Chain analysis.

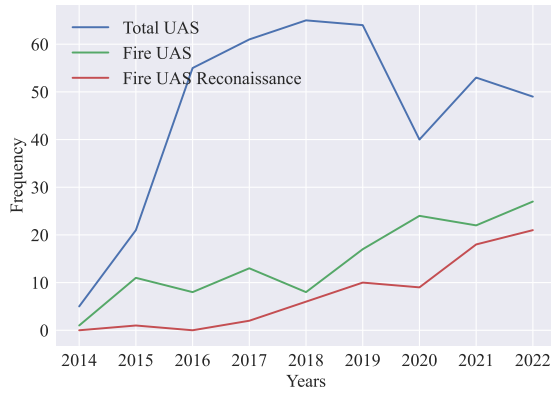


Fig. 3 UAS SAFECOM reports per year, indicating increasing reports over time.

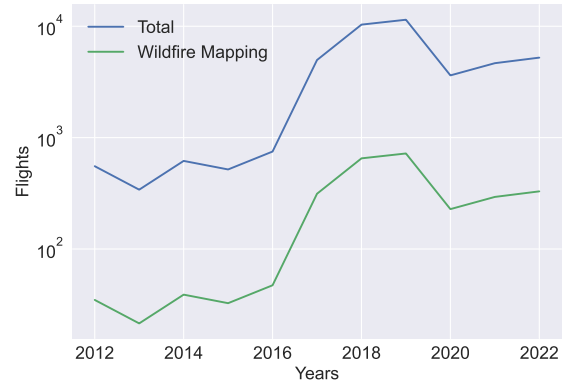


Fig. 4 UAS flights and estimated UAS wildfire mapping mission flights over time.

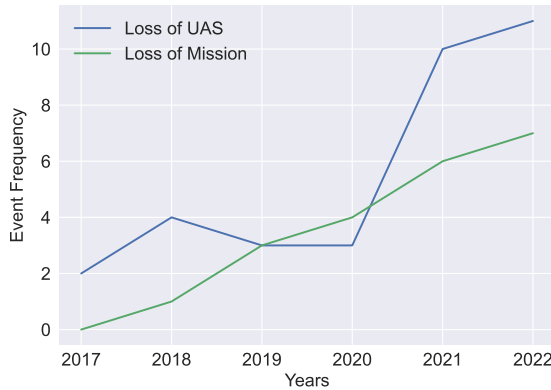


Fig. 5 UAS top events per year, indicating increasing events over time.

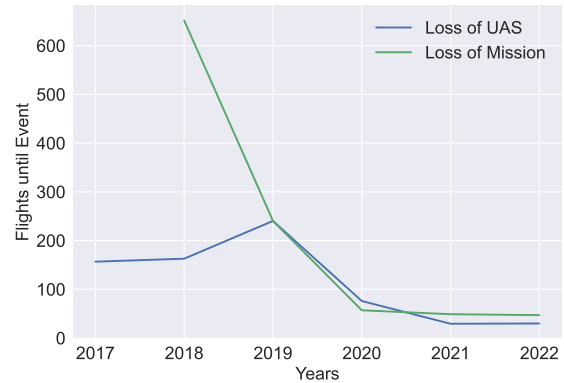


Fig. 6 Number of flights until top event per year.

Table 1 Granular initiating failure events associated with failure categories and frequencies.

Failure Categories	Failure Mode	Frequency
Airspace	Manned Aircraft Intrusion	6
	Airspace Conflict	4
Equipment Failure	Propeller Arm Disconnection	1
	Motor Failure	2
	Motor Mount Failure	1
	Parachute Landing Failure	1
	Battery	4
	Landing Gear Failure	1
	Casing Dislodged	3
	Fasteners Dislodged	2
	Engine Failure	1
	Autonomous Malfunction	2
Human Factors	Miscommunication	1
	Pilot Error	9
	Procedural Error	1
	Inappropriate Landing Site	3
Loss of Control	Control Surface Damage	1
	Loss of GCS	1
	Loss of GPS	4
	Loss of Link	4
	Uncontrolled Flight	12
	High Wind	1
Total		65

Table 2 Top event definitions and frequencies.

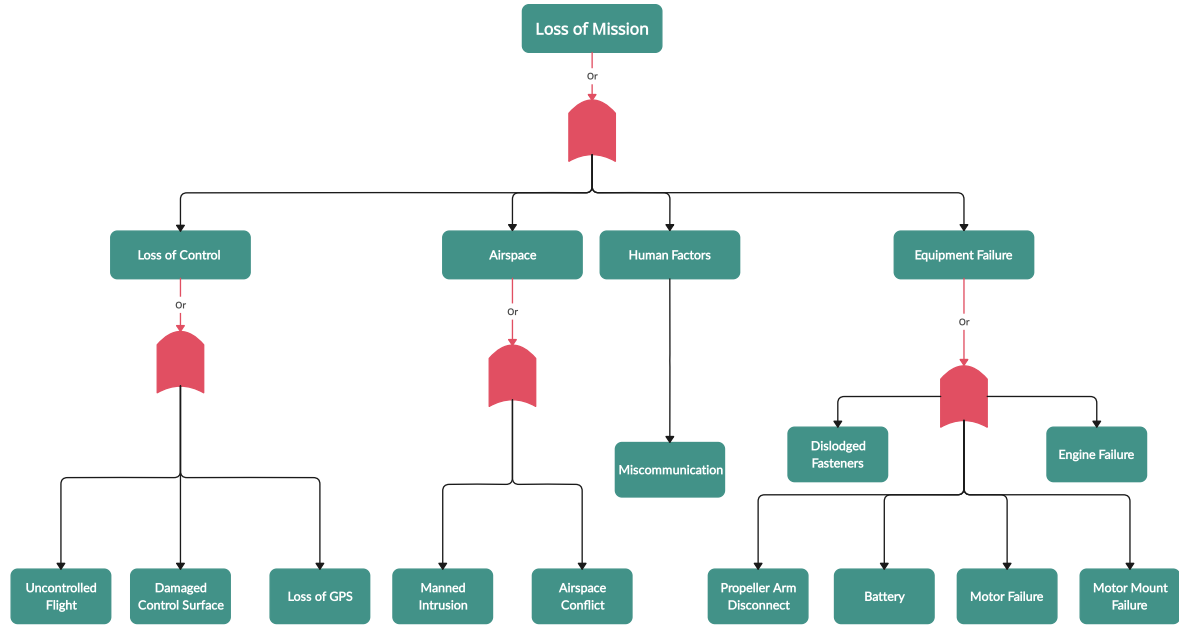
Top Event	Description	Frequency
Loss of Mission	Any outcome or failure mode effect that results in the termination of a current mission or the termination of remaining missions in the day.	21
Loss of UAS	Any outcome or failure mode effect resulting in substantial damage to the UAS requiring off-site repair or complete loss of vehicle.	33
None	Reports that detail no negative outcome with failure mode effects mitigated prior to events occurring.	9
Total		63

B. Fault Tree Analysis

An initial portion of the FTA is available for the two top events, loss of mission and loss of UAS, in Figure 7 and Figure 8 respectively. Of note, loss of UAS top events are caused by a greater variety of equipment failures and loss of control failures than loss of mission top events. That is, severe equipment failures and loss of control of the UAS can lead to circumstances that not only result in the loss of the mission, but also result in the loss of the vehicle itself. Additionally, airspace mishaps have only resulted in loss of mission events.

Table 3 High-level failure category definitions and frequencies.

Failure Categories	Description	Frequency
Airspace	Any initiating event resulting in a failure mode related to airspace non-conformance, including flight path deviations and intrusions.	10
Equipment Failure	Any initiating event resulting in a specific equipment failure mode, including batteries, autonomous navigation, and mechanical components.	18
Human Factors	Any failure mode related to human interaction, including operator errors and communication breakdowns.	14
Loss of Control	Any initiating event resulting in a failure mode related to loss of control of aircraft motion, including high wind, loss of link, loss of GPS, and uncontrolled flight.	23
Total		65

**Fig. 7 Loss of Mission Fault Tree.**

C. Event Tree Analysis

An example of a data-driven event tree generated from the SAFECOM reports for a loss of GPS initiating event is available in Figure 9. After a loss of GPS, the next event could be reconnection or no reconnection. If no reconnection occurs, a UAS could correctly initiate an auto-landing capability, such as return to home, or fail to properly initiate the capability. In the event of an absence of auto-landing or an improper auto-landing, a pilot can attempt to regain control through correct commands. These different paths along the tree can result in nominal operations (i.e., a successful outcome), or top events, such as loss of mission and loss of UAS. Of the four reports on loss of GPS, all resulted in no re-established GPS connection and no correct initialization of auto-landing sequences. Three of the four failed to have correct pilot input commands, including cases of pilots over correcting and manually crashing the UAS, while one report had a successful manual return.

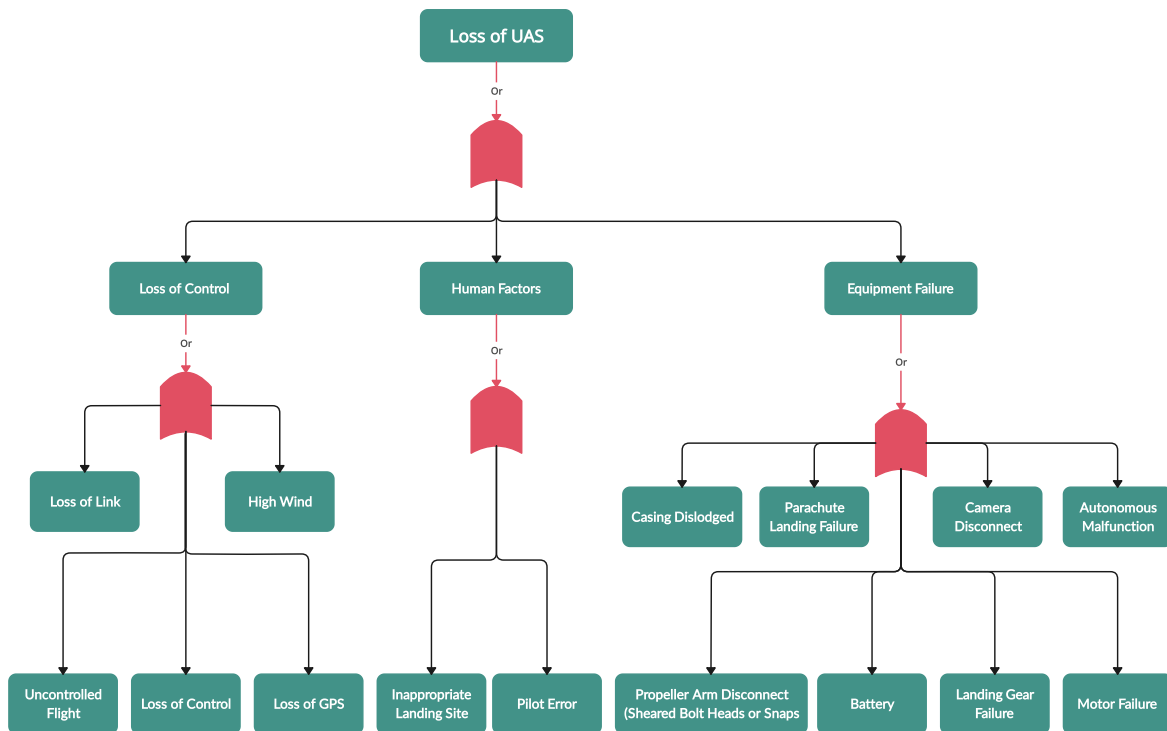


Fig. 8 Loss of UAS Fault Tree.

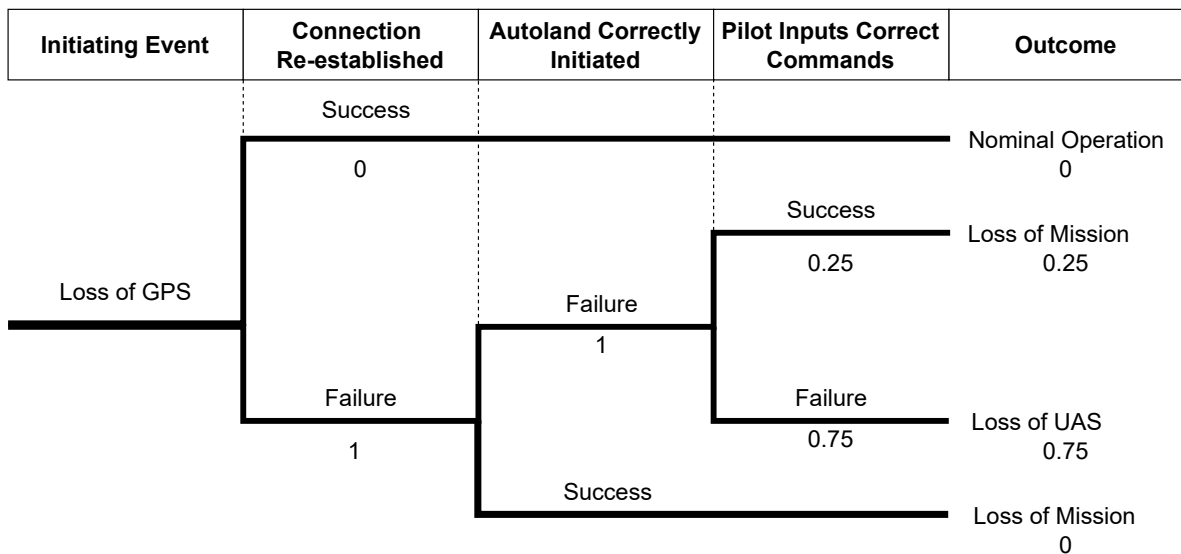


Fig. 9 Loss of GPS event tree.

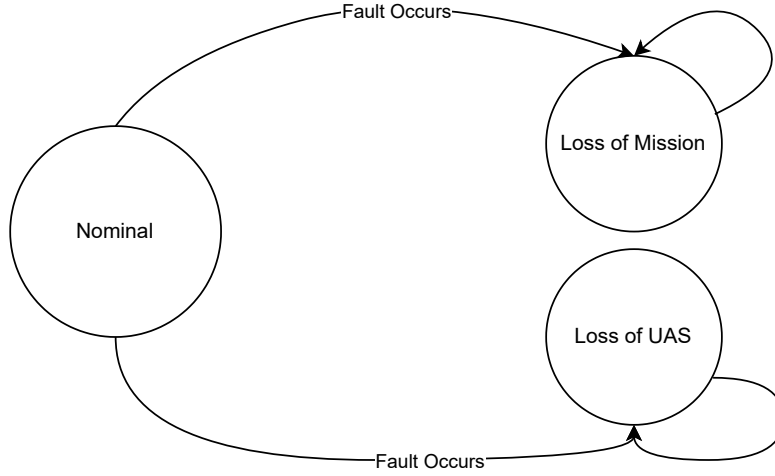


Fig. 10 Markov Chain representation of the system with two top event states.

D. Markov Chain Analysis

To begin the probabilistic risk assessment style analysis with Markov Chains, we first estimate the probability distribution of the number of flights until each top event by estimating the exponential distribution parameters using Equation (4). Using the number of flights until a top event per year in Figure 6, the estimated parameters for loss of UAS and loss of mission are 115.876 and 208.968 respectively. After estimating using bootstrapping on the original samples, the 95% confidence interval for the parameter is [58.659, 179.332] for loss of UAS and [49.799, 448.394] for loss of mission. The estimated, upper, and lower bound probability density functions are shown in Figures 11 and 12, where the lower bound distribution is the case with fewer flights between failures and the upper bounds case has more flights between failures.

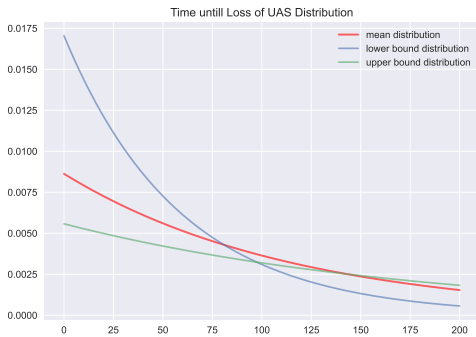


Fig. 11 Time until failure distributions for loss of UAS.

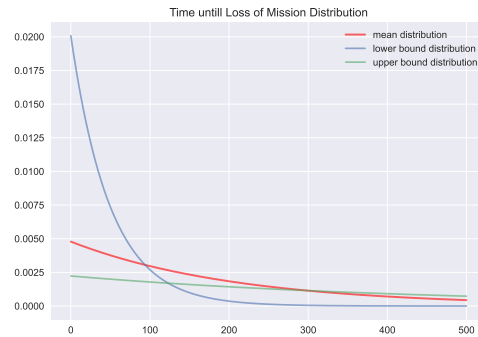


Fig. 12 Time until failure distributions for loss of mission.

Now that we have probability densities for the top events, we can examine the occurrence of the top events using Markov Chains and simulation. A UAS wildfire mapping mission can be viewed as a 3-state Markov Chain with one nominal and two faulty states (loss of UAS, loss of mission) in Figure 10, with faults as absorbing states and nominal as a transient state. A transition from one state to the next is modeled on the time scale of one flight per time step. Thus the chain can be used to evaluate the probability of a faulty state occurring during the next flight and the expected number of flights until a fault occurs. The probability of a faulty state occurring in the next flight is found by taking the cumulative density function of the estimated exponential distributions at the value $x = 1$. Using the probabilities estimated as such,

the Markov Chain can be described by the probability transition matrix, P , in Equation (7), with lower and upper bound transition matrices in Equations (8) and (9) respectively.

$$P = \begin{matrix} & \begin{matrix} \text{Nominal} & \text{Loss of UAS} & \text{Loss of Mission} \end{matrix} \\ \begin{matrix} \text{Nominal} \\ \text{Loss of UAS} \\ \text{Loss of Mission} \end{matrix} & \begin{pmatrix} 0.986 & 0.009 & 0.005 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \end{matrix} \quad (7)$$

$$P = \begin{matrix} & \begin{matrix} \text{Nominal} & \text{Loss of UAS} & \text{Loss of Mission} \end{matrix} \\ \begin{matrix} \text{Nominal} \\ \text{Loss of UAS} \\ \text{Loss of Mission} \end{matrix} & \begin{pmatrix} 0.963 & 0.017 & 0.020 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \end{matrix} \quad (8)$$

$$P = \begin{matrix} & \begin{matrix} \text{Nominal} & \text{Loss of UAS} & \text{Loss of Mission} \end{matrix} \\ \begin{matrix} \text{Nominal} \\ \text{Loss of UAS} \\ \text{Loss of Mission} \end{matrix} & \begin{pmatrix} 0.992 & 0.006 & 0.002 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \end{matrix} \quad (9)$$

Since the system is modeled as a Markov Chain, we can now use the chain properties to estimate the expected number of flights until a faulty state occurs. The system represented in Figure 10 identifies nominal as a transient state, hence the expected time in transient states is equivalent to the expected number of flights until a faulty state occurs. In our system, there is only one transient state (nominal), so the solution to Equation 5 reduces to Equation 10. From this equation, the expected number of flights until a faulty state is 75 flights. Using the same equation for the upper and lower bound transition matrices, the 95% confidence interval for the number of flights until a fault is [27, 125].

$$\begin{aligned} g(\text{nominal}) &= [1 - P(X_{t+1} = \text{nominal} | X_t = \text{nominal})]^{-1} \\ &= [1 - 0.986]^{-1} \\ &= 71 \end{aligned} \quad (10)$$

VI. Discussion

An advantage of this study is that it can be implemented in a dynamic, living PRA manner, rather than a static, one-time analysis. As operations using UAS continue and additional reports become available, new initiating events, failure categories, and top events can be identified and the resulting fault trees, event trees, and Markov chain analysis can be iteratively updated accordingly. This semi-automatic update of previous PRA analyses, along with newly generated safety metrics, can be considered as a capability of an IASMS. Furthermore, additional IASMS services, functions, and capabilities – such as in-time health diagnostic and prognostic, better weather models, state-of-the-art UAS Traffic Management (UTM) – can be designed and operated with these failure modes in mind, and thus, increase overall system safety [40].

The methods in this research are data-driven, thus they rely entirely on the quality and completeness of safety reports. Since the SAFECOM reporting system used in this study is comprised of voluntary reports, the results likely are biased towards an under-representation of the true frequency of top events. Additionally, the number of top events and UAS flights changes from year-to-year, which in turn impacts the probabilistic analysis. The number of flights until a top event is much higher from 2017-2019 than from 2020-2022 for both loss of UAS and loss of mission. In this case, the average failure rate is taken over all the years; however, in some cases it may be more accurate to take the failure rate from only the most recent year(s). Another limitation of this study is the lack of availability of data on flights and flight hours of UAS missions. No data on UAS flight hours was found and we only found data on the number of flights for 2022, resulting in estimations for the number of flights for the remaining years. Nonetheless, the frame work for this analysis can be used if more detailed flight data or different failure rate calculations are provided.

VII. Conclusion

Wildfire incidents continue to be a challenge for wildland fire management professionals and the general population alike. While there are calls to leverage advances in UAS technology to offload risks wildfires pose to firefighters onto UAS, it is of essence that such process is done safely and efficiently, an effort which this study contributes to by analyzing present-day faulty state occurrence. This research presented a data-driven probabilistic risk assessment-styled method to evaluate faulty states with an application to wildfire UAS mapping missions. The method consisted of a hazard identification step, fault tree analysis, event tree analysis, and Markov chain analysis. Using the SAFECOM database and filtering for relevant reports, we identified loss of UAS and loss of mission as the primary faulty top events. The set of possible initiating events leading to each faulty state is enumerated in the fault trees, while an event tree for a loss of GPS initiating event detailed the possible intermediate events and top events following a loss of GPS. From the Markov chain analysis, the estimated number of flights until a faulty state (top event) was found to be 71, with a 95% confidence interval of 27 to 125 flights. This findings describe in detail the occurrence of faulty states in present-day UAS wildfire mapping missions.

Future extensions of this work with focus on implementing natural language processing (NLP) algorithms into the hazard identification step, building off of previous work by the authors [41, 42]. Employing NLP in this step will help assist expert-driven hazard identification and help move towards a more seamless implementation of a dynamic assessment that updates as new reports are made available. Additional Markov chain analysis will also be performed for other sections of the system, including a representation of the event tree analysis as a Markov chain. Programming capabilities will also be built to help verify fault tree and event tree construction based on human-annotated documents.

Acknowledgments

This research is supported by the System-Wide Safety (SWS) project in the Airspace Operations & Safety Program (AOSP) in the NASA Aeronautics Research Mission Directorate (ARMD) and partially funded Under Prime Contract No. 80ARC020D0010 with the NASA Ames Research Center. Any opinions or findings of this work are the responsibility of the authors and do not necessarily reflect the views of the sponsors or collaborators.

References

- [1] Vincenzi, D., Ison, D., and Terwilliger, B., “The role of Unmanned Aircraft Systems (UAS) in disaster response and recovery efforts: Historical, current, and future,” 2014.
- [2] Mbaye, S., Jones, G., and Davies, M. D., *Analysis of Input from Wildfire Incident Experts to Identify Key Risks and Hazards in Wildfire Emergency Response*, 2023. <https://doi.org/10.2514/6.2023-2710>, URL <https://arc.aiaa.org/doi/abs/10.2514/6.2023-2710>.
- [3] An, H., Gan, J., and Cho, S. J., “Assessing Climate Change Impacts on Wildfire Risk in the United States,” *Forests*, Vol. 6, No. 9, 2015, pp. 3197–3211. <https://doi.org/10.3390/f6093197>, URL <https://www.mdpi.com/1999-4907/6/9/3197>.
- [4] Ellis, K. K., Krois, P., Koelling, J., Prinzel, L. J., Davies, M., and Mah, R., *A Concept of Operations (ConOps) of an In-time Aviation Safety Management System (IASMS) for Advanced Air Mobility (AAM)*, 2021. <https://doi.org/10.2514/6.2021-1978>, URL <https://arc.aiaa.org/doi/abs/10.2514/6.2021-1978>.
- [5] Ellis, K., Koelling, J., Davies, M., and Krois, P., “In-time System-wide Safety Assurance (ISSA) Concept of Operations and Design Considerations for Urban Air Mobility (UAM),” Tech. Rep. NASA/TM—2020–5003981, NASA, 06 2020.
- [6] National Academies of Sciences, Engineering, and Medicine, *In-Time Aviation Safety Management: Challenges and Research for an Evolving Aviation System*, The National Academies Press, Washington, DC, 2018. <https://doi.org/10.17226/24962>, URL <https://nap.nationalacademies.org/catalog/24962/in-time-aviation-safety-management-challenges-and-research-for-an>.
- [7] Ellis, K., Krois, P., Koelling, J., Prinzel, L., Davies, M., and Mah, R., “A Concept of Operations (ConOps) of an In-time Aviation Safety Management System (IASMS) for Advanced Air Mobility (AAM),” 2021. <https://doi.org/10.2514/6.2021-1978>.
- [8] Zhou, T., Modarres, M., and Droguett, E. L., “Multi-unit nuclear power plant probabilistic risk assessment: A comprehensive survey,” *Reliability Engineering & System Safety*, Vol. 213, 2021, p. 107782.
- [9] Keller, W., and Modarres, M., “A historical overview of probabilistic risk assessment development and its use in the nuclear power industry: a tribute to the late Professor Norman Carl Rasmussen,” *Reliability Engineering & System Safety*, Vol. 89, No. 3, 2005, pp. 271–285.

- [10] Boyer, R. L., Hamlin, T. L., Grant, W. C., Stewart, M. A., Cross, R. B., Rogers, J. H., and Berrios, A. S., "' Making Safety Happen" Through Probabilistic Risk Assessment at NASA," (*International Association for Advancement of Space Safety*) *IAASS Conference*, 2019.
- [11] Earthperson, A., and Diaconeasa, M. A., "Verification Study of the Nuclear PRA for the Mars 2020 Mission Following Accidental Orbital Re-Entry," *ASME International Mechanical Engineering Congress and Exposition*, Vol. 85697, American Society of Mechanical Engineers, 2021, p. V013T14A019.
- [12] Bonamente, M., *Introduction to Markov Chains*, Springer Nature Singapore, Singapore, 2022, pp. 369–384. https://doi.org/10.1007/978-981-19-0365-6_21, URL https://doi.org/10.1007/978-981-19-0365-6_21.
- [13] Seabrook, E., and Wiskott, L., "A Tutorial on the Spectral Theory of Markov Chains," *Neural Computation*, Vol. 35, No. 11, 2023, pp. 1713–1796. URL <https://direct.mit.edu/neco/article/35/11/1713/117578>.
- [14] FAA, "Safety Management System Policy Order 8000.3698," , 2016.
- [15] "2019 Aviation SMS Guide," Tech. rep., United States Forest Service Fire and Aviation Management, 2019.
- [16] Dezfuli, H., Kelly, D., Smith, C., Vedros, K., and Galyean, W., "Bayesian inference for NASA probabilistic risk and reliability analysis," Tech. rep., 2009.
- [17] Hu, J., Prandini, M., and Sastry, S., "Probabilistic safety analysis in three dimensional aircraft flight," *42nd IEEE International Conference on Decision and Control (IEEE Cat. No. 03CH37475)*, Vol. 5, IEEE, 2003, pp. 5335–5340.
- [18] Yi, L., Zhang, S., Zhang, Z., Zhang, X., Peng, T., and Shan, F., "Multiple hierarchy risk assessment with hybrid model for safety enhancing of unmanned subscale BWB demonstrator flight test," *Chinese Journal of Aeronautics*, Vol. 32, No. 12, 2019, pp. 2612–2626.
- [19] Nepveu, M., Yavuz, F., and David, P., "FEP analysis and Markov chains," *Energy procedia*, Vol. 1, No. 1, 2009, pp. 2519–2523.
- [20] Gorinevsky, D., Hoffmann, G. M., Shmakova, M., Mah, R. W., Cryan, S., and Mitchell, J. D., "Fault tolerance of relative navigation sensing in Docking approach of spacecraft," *2008 IEEE Aerospace Conference*, IEEE, 2008, pp. 1–9.
- [21] Kim, D. J., Sur, J. M., and Cho, H. U., "A long term expected risk estimation of maritime accidents through Markov chain approach and probabilistic risk matrix," *The Asian Journal of Shipping and Logistics*, 2023.
- [22] Federal Wildland Fire Mitigation and Management Commission, "ON FIRE: The Report of the Wildland Fire Mitigation and Management Commission," , 2023. URL <https://www.humanitarianlibrary.org/sites/default/files/2023/10/wfmmc-final-report-09-2023.pdf>.
- [23] United States Forest Services, "The Rising Cost of Fire Operations: Effects on the Forest Service's Non-Fire Work," , 2015. URL <https://www.fs.usda.gov/sites/default/files/2015-Fire-Budget-Report.pdf>.
- [24] Britton, C., Lynch, C. F., Ramirez, M., Torner, J., Buresh, C., and Peek-Asa, C., "Epidemiology of Injuries to Wildland Firefighters," *The American Journal of Emergency Medicine*, Vol. 3994, No. 2, 2013, pp. A1–A10. <https://doi.org/http://dx.doi.org/10.1016/j.ajem.2012.08.032>, URL [http://www.sciencedirect.com/science/article/pii/S0735-6757\(12\)00451-2](http://www.sciencedirect.com/science/article/pii/S0735-6757(12)00451-2).
- [25] Mbaye, S., Jones, G., and Davies, M. D., "Analysis of Input from Wildfire Incident Experts to Identify Key Risks and Hazards in Wildfire Emergency Response," *AIAA SCITECH 2023 Forum*, 2023. <https://doi.org/10.2514/6.2023-2710>, URL <https://arc.aiaa.org/doi/abs/10.2514/6.2023-2710>.
- [26] Twidwell, D., Allen, C. R., Detweiler, C., Higgins, J., Laney, C., and Elbaum, S., "Smokey comes of age: unmanned aerial systems for fire management," *Frontiers in Ecology and the Environment*, Vol. 14, No. 6, 2016, pp. 333–339.
- [27] Lattimer, B. Y., Huang, X., Delichatsios, M. A., Levendis, Y. A., Kochersberger, K., Manzello, S., Frank, P., Jones, T., Salvador, J., Delgado, C., et al., "Use of unmanned aerial systems in outdoor firefighting," *Fire Technology*, Vol. 59, No. 6, 2023, pp. 2961–2988.
- [28] Friedrich, M., Borkowski, M., and Lieb, J., "A multi-UAS platform to accelerate situation assessment in first response missions—identification of user needs and system requirements using design thinking," *2020 AIAA/IEEE 39th Digital Avionics Systems Conference (DASC)*, IEEE, 2020, pp. 1–7.
- [29] Aydin, B., Selvi, E., Tao, J., and Starek, M. J., "Use of fire-extinguishing balls for a conceptual system of drone-assisted wildfire fighting," *Drones*, Vol. 3, No. 1, 2019, p. 17.

- [30] Barr, L. C., Newman, R., Ancel, E., Belcastro, C. M., Foster, J. V., Evans, J., and Klyde, D. H., "Preliminary risk assessment for small unmanned aircraft systems," *17th AIAA Aviation Technology, Integration, and Operations Conference*, 2017, p. 3272.
- [31] Pettersson, M. N., Axelsson, J., Svenson, P., and Johansson, A., "Towards a Risk Analysis Method for Systems of Systems: A Case Study on Wildfire Rescue Operations," *20th Global Information Systems for Crisis Response and Management Conference, ISCRAM 2023; Conference date: 28 May 2023 through 31 May 2023*, Information Systems for Crisis Response and Management, ISCRAM, 2023, pp. 530–545.
- [32] Janik, P., Zawistowski, M., Fellner, R., and Zawistowski, G., "Unmanned aircraft systems risk assessment based on sora for first responders and disaster management," *Applied Sciences*, Vol. 11, No. 12, 2021, p. 5364.
- [33] Hejase, M., Kurt, A., Aldemir, T., Özgüner, Ü., Guarro, S. B., Yau, M. K., and Knudson, M. D., "Quantitative and risk-based framework for unmanned aircraft control system assurance," *Journal of Aerospace Information Systems*, Vol. 15, No. 2, 2018, pp. 57–71.
- [34] White, G., "Evaluation of systems to recognise and address safety issues promptly, effectively and universally and evaluation of systems which promote safe fire fighting behaviours and initiatives." Tech. rep., Department of Natural Resources and Environment, 2002.
- [35] Department of the Interior, "SAFECOM Aviation Safety Communiqué," <https://www.safecom.gov/>, 2023. Accessed: 2023-10-16.
- [36] United States Department of the Interior, Office of Aviation Services, "Department of the Interior / USDA Forest Service Fiscal Year 2022 Uncrewed Aircraft Systems Interactive Report," , 2022.
- [37] United States Department of the Interior, Office of Aviation Services, "FY 2022 DOI Aviation Safety Summary and Annual Report," , 2022.
- [38] Ericson, C. A., and Li, C., "Fault Tree nAlysis," *System Safety Conference, Orlando, Florida*, Vol. 1, 1999, pp. 1–9.
- [39] Stamatelatos, M., and Vesley, W. E., "Fault Tree Handbook with Aerospace Applications," 2002. URL <https://api.semanticscholar.org/CorpusID:61105226>.
- [40] Moore, A. J., Young, S., Altamirano, G., Ancel, E., Darafsheh, K., Dill, E., Foster, J., Quach, C., Mackenzie, A., Matt, J., Nguyen, T., Revolinsky, P., Smalling, K., Vazque, S., Martin, L., Feldman, J., Gujral, V., Spirkovska, L., Hooey, B., Bradner, K., Iverson, D., Wolfe, S., Oza, N., Condotta, R., Morris, C., Glover, J. S., Rymer, N., Turner, A., Walter, C., Banerjee, P., Corbetta, M., Kulkarni, C., Cleland-Huang, J., Jones, J., and Bonin, T., "Testing of Advanced Capabilities to Enable In-time Safety Management and Assurance for Future Flight Operations," Tech. Rep. NASA/TM–20230018665, NASA, 04 2024. URL <https://ntrs.nasa.gov/citations/20230018665>.
- [41] Andrade, S., and Walsh, H. S., "Natural-Language-Processing-Enabled Quantitative Risk Analysis of Aerial Wildfire Operations," *Journal of Aerospace Information Systems*, Vol. 21, No. 2, 2024, pp. 114–126. <https://doi.org/10.2514/1.I011243>, URL <https://doi.org/10.2514/1.I011243>.
- [42] Andrade, S. R., and Walsh, H. S., "Machine learning framework for Hazard Extraction and Analysis of Trends (HEAT) in wildfire response," *Safety Science*, Vol. 167, 2023, p. 106252. <https://doi.org/https://doi.org/10.1016/j.ssci.2023.106252>, URL <https://www.sciencedirect.com/science/article/pii/S0925753523001947>.