A Future In-time Aviation Safety Management System (IASMS) Perspective for Commercial Air Carriers

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Today's commercial air carriers ensure safety through use of Safety Management Systems (SMS) although traditional SMS is labor-intensive and has difficulty scaling with the increasing complexity of operational data. An In-time Aviation Safety Management System envisions the integration of risk management and safety assurance using machine learning to timely monitor, assess, and mitigate known risks and detect emergent risks. This innovative perspective enables proactive and predictive safety using data analytics for improved actionable safety intelligence and risk visualization.

I. Introduction

Technology innovations, market forces, and new opportunities compel continuous change to the National Airspace System (NAS) foreseen in the National Aeronautics and Space Administration (NASA) Sky for All vision [1] and the Federal Aviation Administration (FAA) concept for 2035 [2]. Safety remains paramount as the topmost priority to ensuring the successful advancement of aviation coupled with the need to overcome challenges and constraints both in design and operations. While today's overarching Safety Management System (SMS) has provided benefits of reduced aviation accidents and incidents, envisioned future concepts of operations potentially present new safety challenges. For example, significantly more vehicles are projected to be flying in closer proximity to other aircraft, including some vehicles that may be piloted remotely or by automated systems within the same airspace as crewed aircraft. To address this concern, a new perspective for safety management is needed. The new perspective the National Academies recommended is an In-time Aviation Safety Management System (IASMS) to ensure a safe future NAS [3].

The purpose of this paper is to examine how a future IASMS could benefit today's commercial air carriers with the IASMS concept of operations (ConOps) providing a critical juncture for improving risk management and safety assurance beyond how SMS has generally been implemented [4, 5]. As part of the NAS, commercial air carriers are in effect responsible for implementing SMS. The evolution of today's SMS to an IASMS can take multiple paths and involve different aspects, recognizing that air carriers have different approaches and methods for implementing SMS to show compliance with FAA SMS regulations. To transform its SMS to the IASMS, an air carrier needs the ability to fuse and evaluate increasingly large, disparate sets of data to quickly (in-time) identify and mitigate risks and hazards in ever increasingly complex operations while integrating process changes to advance safety intelligence. This paper complements previous papers addressing IASMS with other aviation domains, such as Advanced Air Mobility (AAM) [4, 5] and space launch and reentry [6].

Key attributes of the IASMS ConOps addressed by this paper are the integration of different sources of operational data for use in predictive analytics, based on data fusion with in-time decision making and execution; system modeling; human-system integration best practices; safety intelligence; and a new concept termed "learning from all operations." The paper concludes by identifying emerging opportunities to demonstrate how IASMS can strengthen air carrier safety management.

II. SMS for Air Carriers

The traditional framework of SMS was established by the International Civil Aviation Organization (ICAO) [7]. ICAO defines an SMS as, "a systematic approach to managing safety, including the necessary organizational structures, accountability, responsibilities, policies, and procedures." The traditional State Safety Program (SSP) framework of an SMS, outlined in ICAO Annex 19 (2nd edition) informed by ICAO Standards and Recommended Practices (SARPS), is comprised of the four pillars: (a) Safety Policy and Objectives, (b) Risk Management, (c) Safety Assurance, and (d) Safety Promotion. SARPS form the foundation of a safe global aviation system, and the safety management SARPS and SMS pillars are intended to help manage commercial aviation safety risks, in coordination with their aviation service providers. ICAO "Safety Management Manual" (Document 9859) provides guidance material on safety management principles and concepts, the SSP, and SMS implementation intended to support the continued evolution of safety management and the SSP of each ICAO State, such as the FAA, in accordance with provisions of Annex 19 [8].

Title 14 of the Code of Federal Regulations (14 CFR) Part 5 requires implementation of SMS by Part 121 Aviation Service Providers (i.e., commercial air carriers). The regulation identifies the basic processes integral to an effective SMS but does not specify the methods for how to implement these processes. All SMS requirements are applicable to an air carrier regardless of its size. The FAA provides guidance and methods for developing and implementing an SMS to demonstrate means of compliance in Advisory Circular (AC) 120-92B titled "Safety Management Systems for Aviation Service Providers" [9].

AC 120-92B provides an SMS framework, shown in Figure 1, that integrates the processes for risk management and safety assurance. Safety risk management (SRM) involves early identification of hazards and ensuring controls are designed to manage known hazards at an acceptable level. Safety assurance (SA) monitors performance for how controls are used operationally to confirm that risk is mitigated as intended. Loops between risk management and safety assurance include the operational monitoring of risk controls to validate their efficacy and monitoring of operational data for emergent or different hazards that require new risk controls or a change to them.

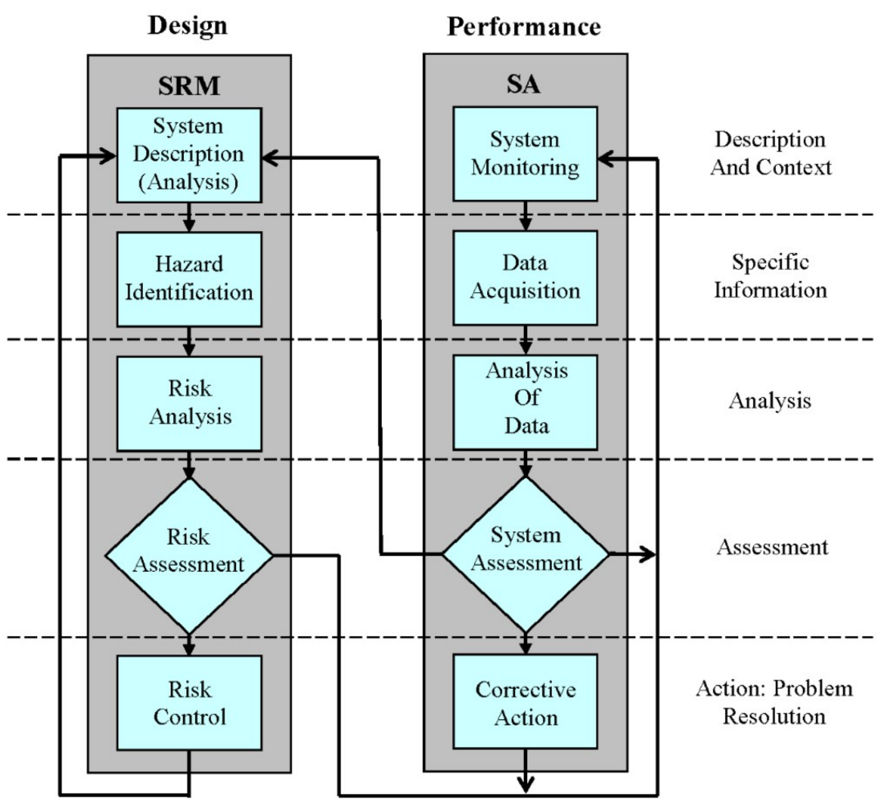

Fig. 1 FAA SMS Framework for Part 121 Air Carriers (from AC 120-92B, Figure 2.1).

For safety assurance, AC 120-92B identifies methods for flight-by-flight monitoring of operational performance of systems and their associated risk controls that can be used by commercial air carriers. A carrier has the option to devise other method(s) to show means of compliance. The methods and sources of operational performance data identified in AC 120-92B include the following:

1) Line Operations Safety Audit (LOSA) in which qualified observers, typically carrier pilots, ride the jump seat during regularly scheduled flights to observe and record safety-related data on various weather and visibility conditions, operational complexities, and flight crew performance. LOSA uses the Threat and Error Management (TEM) model to classify safety threats to flight operations, human errors, and unsafe conditions either mitigated or not resolved during the flight.
2) Advanced Qualification Program (AQP) involves a methodology systematically applied for developing training program components for flight crew members and dispatchers. An AQP incorporates data-driven quality control processes for validating and maintaining the effectiveness of curriculum content.
3) Aviation Safety Reporting System (ASRS) is the program developed and managed by NASA, as an independent third party, for pilots and other aviation professionals to submit aviation safety reports voluntarily and anonymously. Aggregation and analysis of ASRS data provides only global systemic information where the level of detail constrains analysis of specific systems and processes.
4) Flight Operational Quality Assurance (FOQA) is a program involving the routine collection of digital flight data generated during aircraft operations that are then download post-flight and analyzed. FAA published AC 120-82, "Flight Operational Quality Assurance," that provides guidance and means of compliance for FOQA program development, implementation, acceptance, and operation [10].
5) Aviation Safety Action Program (ASAP) provides for voluntary reporting of safety issues and events by the air carrier's employees. While the air carrier would analyze each report and ascertain whether corrective action is needed for it, the operational safety assurance process includes analysis of patterns across reports that could identify systemic problems. To support the requirement of a confidential reporting system, FAA developed AC 120-66, "Aviation Safety Action Program," to provide guidance for ASAP development, implementation, acceptance, and operation [11].
6) Internal Evaluation Program (IEP) is a safety process comprised of inspections, audits, and evaluations configured to assess the adequacy of managerial controls and processes in critical safety systems. The IEP intends to increase awareness management and employees' responsibility to follow company safety practices and comply with all regulatory requirements.
7) Continuing Analysis and Surveillance System (CASS) is a quality assurance system that monitors and analyzes the performance and effectiveness of the air carrier's Continuous Airworthiness Maintenance Program (CAMP).

SMS can be scaled for different types and sizes of operators and their different business models. Air carrier sizes are categorized into small (fewer than 10 airplanes), medium (fewer than 48 airplanes), or large (more than 48 airplanes). Complexity of operations corresponds to the size due to the volume of data available, the size of the employee workforce, and the resources needed to manage the organization.

Air carriers typically protect their SMS systems as proprietary and many domestic U.S. carriers, Part 135 cargo delivery companies, and other stakeholders share their SMS data through an entity managed by the FAA called the Aviation Safety Information Analysis and Sharing (ASIAS) system. ASIAS was devised to improve NAS-wide safety by transitioning from a reactive, forensic investigation approach identifying causal factors of accidents and incidents and preventing their reoccurrence to a diagnostic/prognostic approach. ASIAS accomplishes this by aggregating data across carriers to see how certain rare events could be indicative of systemic problems and identify emerging safety issues that may otherwise be undetectable through data sources at individual carriers.

A broad perspective on SMS was developed by the Civil Air Navigation Services Organization (CANSO) in its standard of excellence in SMS [12]. CANSO's approach aligns with ICAO and provides guidance that an air navigation service provider (ANSP) can follow to meet or exceed ICAO regulatory requirements including adapting the guidance to accommodate its size and operational complexity. The standard uses a model consisting of a system enabler (safety culture) and a framework of five components addressing 16 elements, as shown in Figure 2.

Fig. 2 CANSO SMS Model.

III. Shortfalls and Evolution of Today's SMS

One key challenge for today's SMS to continue assuring safety in the NAS is the public's low tolerance for accidents and fatalities, as reflected by highly publicized aircraft accidents, airport runway near-misses, and other incidents [13, 14, 15]. In support of its advocacy of aviation safety, ICAO, in its Global Aviation Safety Plan (GASP), called to "achieve and maintain aspirational safety goal of zero fatalities for global commercial operations by 2030 and beyond" [16]. The purpose of the GASP "is to continually reduce fatalities, and the risk of fatalities, by guiding the development of a harmonized aviation safety strategy and developing and implementing regional and national aviation safety plans." ICAO guidance on how to address current organization challenges and aviation high-risk categories of occurrence and "global safety priorities" is also provided in the Global Aviation Safety Roadmap (GASR) [16, Appendices A and B, 17]. The GASR provides a structured, common frame-of-reference action plan to achieve global aviation safety goals developed by a consortium of international safety organizations and serves as an implementation program for ICAO's GASP. Included in these goals are calls for more effective SMS implementation to support the reduction of operational safety risks and strengthen safety oversight capabilities. ICAO provides a detailed description of the critical elements of regulator safety oversight functions requisite to SMS, to include system and functions; technical guidance, tools, and the provision of safety-critical information; surveillance obligations; and resolution of safety issues [16, section 3.2.1].

Another key challenge is that today's SMS is labor-intensive with humans collecting, integrating, and assessing diverse data from multiple systems having different capabilities and identified known and emergent risks up leveled through a series of operational safety teams for further review and analysis. This sequential process correlates findings across data sources and advances through different management risk mitigation boards for review and decision making.

There is also a key challenge that today's SMS has limited ability to scale due in part to the complexities of data sources that are not easily integrated. The ability to fuse and integrate these data is seminal to developing predictive analytics and use of Machine Learning (ML) to identify and model anomalies, precursors, and trends as well as detect emergent risk.

Overall, the shortfall with today's SMS is its inability to quickly monitor, integrate, and assess large data sets to identify known as well as emergent risks in-time so that contingencies can be determined, and mitigations implemented expeditiously.

As a complementary component of SMS and IASMS, the evolution of ASIAS, as shown in Figure 3, is planned as an increasingly complex data architecture. This architecture enables leveraging data fusion capabilities and use of predictive analytics associated with ML, which is considered a subfield of artificial intelligence. Each phase in the evolution of this architecture is expected to increase the effectiveness in discovering aviation vulnerabilities by tightly integrating automated processes with the expertise of human subject matter experts (SMEs). ASIAS 3.0 introduces faster sharing of data to enable more rapid decisions for mitigation of vetted and valid risks. Moreover, the added "in-time" parameter that IASMS could bring would advance risk identification and mitigation to the operational leading edge.

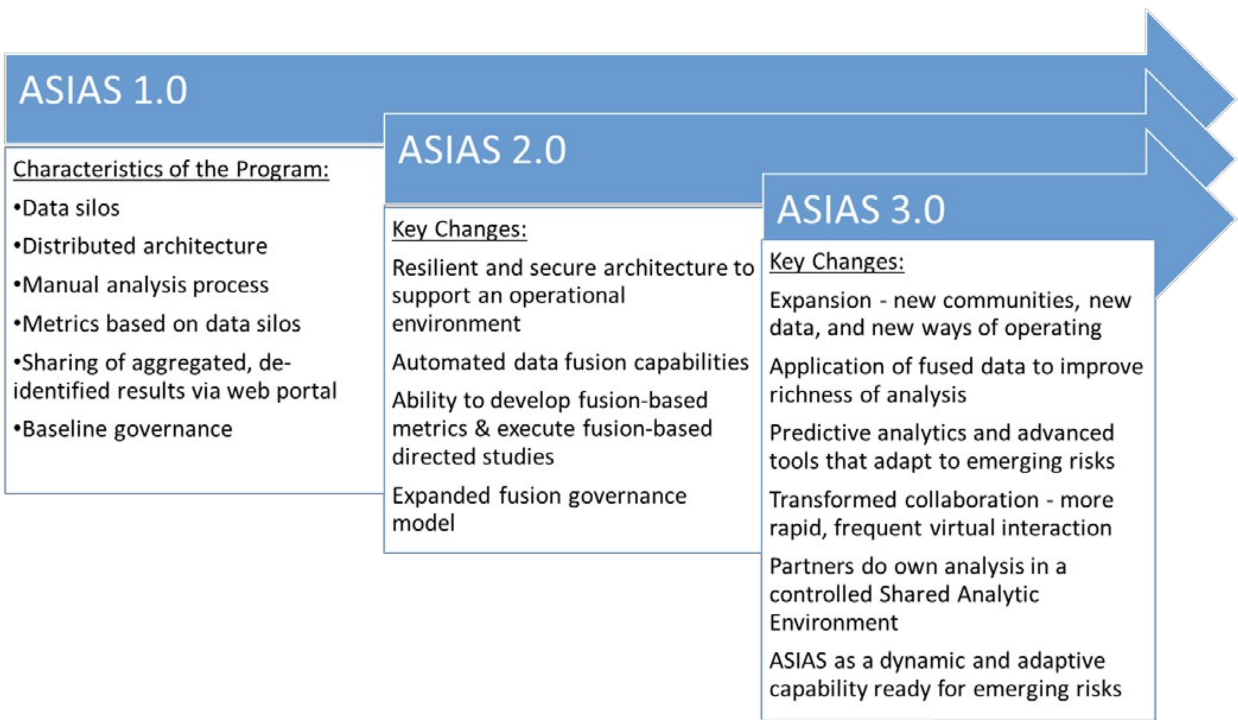

Fig. 3 Evolution from ASIAS 1.0 to ASIAS 3.0 [18].

IV. IASMS ConOps

The IASMS as considered by the National Academies incorporated NASA's focus on in-time system-wide safety assurance (ISSA) for aviation transformation. The NASA Aeronautics Research Mission Directorate (ARMD) Strategic Thrust 5 (see https://www.nasa.gov/aeroresearch/strategy) involves in-time safety assurance through domain-specific safety monitoring and alerting tools, integrated predictive technologies with domain-level applications, and in-time safety threat management. Part of the intersection of Thrust 5 with the NASA "Sky for All" Vision 2045 concerns the longer-term goal to develop an automatically assured adaptive in-time aviation safety management system [1]. The system is characterized by in-time safety intelligence through integrated threat monitoring, detection, prediction, and mitigation processes in the envisioned future highly dynamic, complex, and uncertain airspace ecosystem. A path identified for achieving this future view of how safety is managed and assured in-time has been conceptualized into this new type of commercial aviation SMS called IASMS. The Sky for All vision is to accelerate the transformation to a digitally integrated air transportation system that enables access and increases mobility for all users.

The IASMS ConOps initially focused on the two pillars of risk management and safety assurance most closely related to the National Academies recommendations. Figure 4 represents the evolution of the ICAO original 4-pillar SMS with the envisioned integration of risk management and safety assurance with IASMS. This integration is achieved with the paradigm of key functions of monitor, assess, and mitigate [4, 5]. Prior to the IASMS ConOps, the ConOps for ISSA addressed only the risks within the urban air mobility (UAM) domain. With a widening perspective, the IASMS ConOps adjoins all four SMS pillars as applicable to air carriers and all other domains of the NAS.

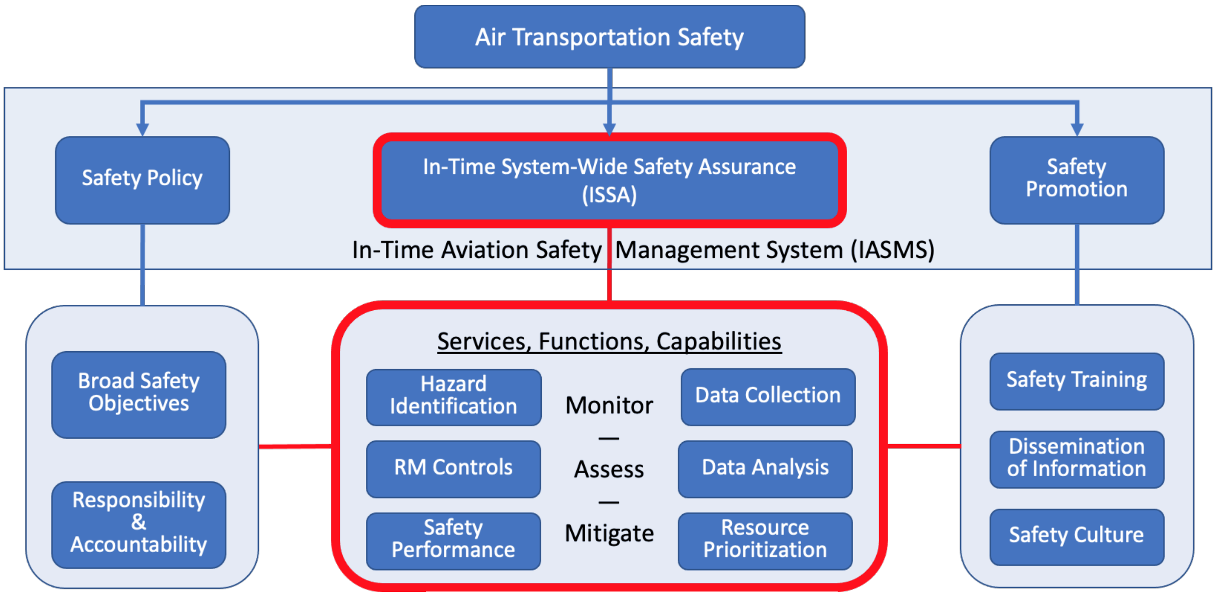

Fig. 4 SMS Framework for IASMS.

While IASMS is considered to be complementary to ASIAS 3.0 in sharing the characteristics for Part 121 commercial air carriers relative to data fusion and predictive analytics, IASMS involves an architecture for the in-time identification, assessment, and mitigation of risk with human-autonomy teaming that scales with the design and operation of ever increasingly autonomous systems in the NAS. The evolution of the NAS as represented by the FAA Vision 2035 and NASA Vision 2045 involves epochs that transition from today's trajectory-based operations, with automated in-time safety monitoring and alerting services, to future performance-based, collaborative air traffic management (ATM) involving third-party service providers and integrated predictive risk identification and mitigation across domains (2035). It then phases to highly automated ML-based dynamic, robust performance, and safety with automatically assured adaptive in-time safety threat management (2045).

V. IASMS Predictive Analytics

Increasingly complex aviation safety issues necessitate new analytic methods and tools to identify complex patterns and detect emergent risks. The objective is to rapidly discover patterns in data that may predict negative outcomes before the next safety event occurs. Air carriers would benefit from development of technologies that integrate and fuse large, disparate sets of data from multiple sources. The approach enables the execution of a system-wide risk assessment to help achieve in-time system-wide safety threat management. ML fuses and interprets complex patterns in data that might otherwise appear as insignificant. This improved speed and characterization of system-wide risk identification would augment existing SMS processes supporting risk management and safety assurance.

Predictive safety management is concerned with identifying possible risks in a situation based on given circumstances and anticipating needed risk controls. Proactive safety management identifies root causes that can lead to hazard occurrence as well as drift in operational practices away from nominal patterns or procedural requirements. Reactive safety management identifies specific causal and contributing factors of an incident or accident, both in design and operations, and develops mitigations to reduce the potential for those factors to lead to another incident or accident. Current SMS practices by air carriers tend to rely on reactive safety management to address issues as they occur, and with some bridging of proactive safety management. For example, data from the FOQA program that collects and aggregates data post-flight are analyzed for possible trends in flight operational performance data.

Predictive analytics builds on advanced methods for data-driven anomaly detection using ML. Data-driven anomaly detection, coupled with domain expert feedback on the operational significance of the identified off-nominal conditions, can effectively identify operationally significant anomalies during operations and provide explanations for them. Precursor identification methods can be used by domain experts to identify precursors to known, undesirable safety events. These approaches enable effective teamwork between human domain experts and ML to identify sequences of events that lead to anomalous operations and can lead to increasing trust in autonomous systems. Effective concepts and principles in human teaming with autonomation and autonomy, as well as human-system integration, will be important to achieving trust. Research poses that ML algorithms should be considered complementary and multiple algorithms will need to be integrated to use their respective strengths [19, 20, 21]. Analytic techniques from other AAM domains may be extensible to Part 121 air carriers such as with data-driven anomaly detection [22, 23].

Human feedback and input are critical to increase the effectiveness of ML. This human feedback could be an assessment of whether a statistical anomaly found by a data-driven anomaly detection algorithm is a safety issue or not. Human feedback could also be a description of the state of the system based on the nature of data collected or any subset of it. Such feedback allows for a higher-level representation of the system state which is easier for humans to understand and helps the explainability, explicability, observability, and verifiability of ML. For example, rather than always viewing FOQA data in terms of the raw data, it can be viewed in terms of time-based sequences of states (e.g., cruise to top-of-descent to initial descent and so forth). Research has demonstrated the challenge humans have understanding the subset of ML methods that are non-deterministic, "black box" methods that can lead to less than desired human-machine interaction including over-trust/overreliance and complacency due to the high cognitive overhead associated with these data analytical methods, particularly for safety sensitive/critical use [24, 25]. Therefore, human in-the-loop is also posited to help mitigate potential for human factors "use, misuse, disuse, and abuse" issues. Also, it addresses IASMS design challenges with increasingly autonomous systems that have higher-then-expected incidences of poor human-automation interactions that may compromise safety.

An example of the first type of human feedback described in the previous paragraph is an assessment of the significance of anomalies found using data-driven anomaly detection methods. Such anomalies are abnormal only in the statistical sense that they are outliers, i.e., they may or may not represent a safety event. Therefore, after an algorithm produces a list of statistical anomalies, an SME must review the list to identify the few statistical anomalies that are operationally relevant for further investigation. The time spent reviewing the statistical anomalies that are not safety-relevant is not productive time. Active learning is a branch of ML that works to minimize SME labeling time by finding the statistical anomalies for which labels would be most informative and decrease the false alarm rate of the anomaly detection algorithm.

The active learning method builds a classifier that can distinguish between operationally significant and uninteresting anomalies with 70% fewer labels compared to manual review while achieving comparable accuracy [26, 27]. The result of the active learning approach is a significant enhancement of ML algorithms through teamwork with SMEs to discover potential safety threats before they emerge as risks. Finding anomalies alone is not sufficient. For both known and unknown safety issues, it is necessary to find their precursors that are states of the system that are not safety issues themselves, but which increase the probability of safety issues. For example, one precursor identification algorithm involved identifying precursors to go-arounds, including potential overtake situations and excessive airspeed on approach, which was able to find definitions of these precursors (e.g., what constitutes "excessive airspeed") specific to the relevant conditions (e.g., the assigned landing runway). Three algorithms for precursor identification have been developed that are increasingly sophisticated in being able to use available information. As with anomaly detection algorithms, it is expected that new precursor identification algorithms will be developed, and their strengths leveraged as part of an IASMS.

ML algorithm developments represent key steps in providing data analytics necessary for both "in-time" and "predictive" safety management. These methods, tools, and techniques can discover data patterns and yield insights not otherwise possible with traditional SMS safety assessments and, moreover, with efficacy superior to previous ML algorithms. Importantly, currently only a small fraction of available safety data is mined (and those that are often have time latencies in event occurrence, assessment, and any mitigation actions). Therefore, it is further posited that the forecasted increase in big data will necessitate the use of NASA-developed ML data analytical methods to provide another critical support to SMS evolution—the concept of aviation safety "learning organizations" and the relationship between "learning from all operations" and "in-time prognostic predictive safety intelligence."

As an example, one study examined an initial machine learning method that predicted unstable high energy landing (long or hard) with 80% accuracy. The air traffic controller could be alerted about a potentially unstable high energy landing situation and recommend a go-around to the flight crew. Another study called VIPR examined precursors to in-flight engine incidents [28]. Depending on the nature of the engine problem, VIPR was able to detect serious fault conditions in flights prior to the incident. Precursors were detected to an in-flight engine shutdown about 30 flights prior to that incident, to a flight engine shutdown caused by high vibration event about 20 flights prior to that incident, and to an engine on-fire safety incident some 4 to 5 flights prior to that incident.

A. In-Time Predictive Safety Intelligence

A question that has been proposed to the aviation safety community is, "what if the aviation industry could identify threats and mitigate safety risks before they occur?" For example, the aircraft Flight Management System (FMS) is comprised of systems having varying levels of automation and it was reported that LOSA data showed that 20% of flights necessitate the pilot taking action to handle aircraft malfunctions, only 10% of flights are completed based on the original flight plan entered into the FMS before departure, and about 35% of flights involved FMS programming errors [29]. Increasingly complex aviation safety issues necessitate more robust safety intelligence built on new analytic methods and tools to identify complex patterns and detect emergent risks. ML can fuse and interpret complex patterns in data that might otherwise appear as weak signals and not be recognized by the human SME. Research has been tackling the problem by introducing ML methods into complex, data-informed decision making to help identify actionable data, recognize patterns, predict mitigation actions, yield new hidden safety insights, and assure safety. Because of the ever-increasing volume of disparate data, the path to predictive SMS is challenged by the need for data analytics that can evaluate and detect unknown vulnerabilities and discover precursors, anomalies, and other predictive indicators, as compared to more traditional safety metrics used (e.g., FOQA exceedances). These vulnerabilities are "needles in a haystack" that ML methods are ideally suited to discover.

The use of ML to improve aviation safety is not new. Application of ML and other current and emerging data-driven approaches have already contributed to enhancing safety of flight operations. For example, ML has been applied to development of new runway overrun protection systems designed to help prevent runway excursions, veer-offs, and other undesired aircraft states upon landing and roll-out. Moreover, for proactive and predictive safety systems, the substantial increase in amount of data available continues to provide the opportunity and impetus to utilize ML and data mining techniques, with modern airliners having more than 50,000 sensors collecting 2.5 terabytes of data daily. The evolution to predictive SMS and the increasing complexity of operations will increase the volume, velocity, veracity, and variety of data produced and the need for ML to understand and act upon these data. With this growth of predictive safety intelligence comes the challenges of integrating new data streams that are not easy to access and failure to integrate useful technologies due to programmatic roadblocks.

VI. Safety Intelligence

The IASMS provides a common path for air carriers to develop a vision for safety intelligence and learning from all operations. Learning from all operations is cross-cutting to the ICAO SMS pillars and offers new opportunities to add to the breadth of data available to a variety of data repositories [30]. Such data could be used to augment risk management and safety assurance processes by informing new safety enhancements with key insights and lessons learned of what has been done to avoid risks in similar circumstances. All participating parties would share safety information and data such as across FAA and ASIAS, ICAO, International Air Transport Association (IATA), and other stakeholders.

Safety intelligence is a key attribute of IASMS and how it pertains to different aspects of the NAS. Air carriers can assess the benefits and limitations of IASMS as the business case for compliance with SMS pillars. The business scope includes identifying and prioritizing uses of, and refinements to, predictive analytics and prototype data decision dashboards. Capabilities such as these can enable human safety intelligence and learning from all operations to strengthen compliance with SMS pillars. In particular, safety policy and safety promotion could be more closely bridged through IASMS to more effectively advance organizational continuous learning approaches involving proactive and predictive safety intelligence.

Safety intelligence builds on predictive analytics and ML. The expected increase in demand for digital data for predictive analytics and ML is not limited to enabling new operations as a critical part of transforming the future aviation system safely. Today's air carriers with their existing safety management systems will need to evolve their safety business strategies to take advantage of the anticipated increased data volume using an architecture designed to provide for access and data aggregation. These strategies will also seek to take advantage of opportunities that may be afforded by new data analytical methods and novel ways of system safety thinking.

Safety intelligence is inherent to the IASMS architecture with services, functions, and capabilities (SFCs) that integrate risk mitigation in design with operational safety assurance. In addition, to meet airworthiness standards for Part 25 transport category aircraft, learning from all operations and safety intelligence provide a lens to assess and validate designed risk mitigation controls, identify related changes to operational procedures and training, and improve dissemination of SMS information and safety culture. The SFCs that develop with the IASMS architecture will add primarily automated sources of information with options for assessment and mitigation within the flow of risk management and safety assurance (see Fig. 1) [31].

As part of the building blocks for developing safety intelligence and continuous learning, ICAO SMS provisions use of the following:

1) Proactive safety activities to collect safety information and safety data
2) Proactive methods for hazard identification
3) Predictive safety indicators focused on processes and activities to improve and maintain safety
4) Predictive analysis based upon current operations

For safety risks to be identified from patterns in precursors, anomalies, and trends in new types of data and the increased volume of data, SFCs are required that enable predictive safety management with its new data analytical methods and novel ways of system safety thinking. Safety risks may appear as validated concerns known to designers and operators and known to be detected and mitigated by assured SFCs (i.e., knowns). Emergent risks may be new and heretofore unknown to designers and operators (e.g., an unexpected and surprising situation) but SFCs could understand, adapt, and manage them through ML. Other emergent risks could be recognized by designers or operators even though these are outside the envelope for assured SFCs to detect and mitigate them. Lastly, there could be unforeseen risks that are not recognizable by designers or addressed in training and procedures for pilots and maintenance technicians, or by safety assurance SFCs and await discovery (unknowns).

Another part of the building blocks for conceptualizing development of safety intelligence and continuous learning in IASMS involves considering systems for reactive, proactive, and predictive safety management. The IASMS SFCs provide for faster and more responsive protections and mitigations using proactive hazard identification and predictive safety indicators [31]. These multiple channels provide critical understanding, analysis, and design of IASMS for monitoring, assessing, and mitigating risk.

Airline SMS was initially designed as an entirely reactive response to safety events and has evolved today through the ICAO SMS pillar of Safety Promotion into a more proactive safety management approach for risk identification, mitigation, and assurance. Gaining international community consensus among safety organizations focused on SMS and achieve an effective IASMS will require a range of assured SFCs to enable predictive safety management. ICAO Annex 19 and Safety Management System document 9589 already provide provisions for the use of (a) proactive safety activities to collect safety information and safety data, (b) proactive methods for hazard identification, (c) predictive safety indicators focused on processes and activities to improve and maintain safety, and (d) predictive analysis based upon current operations [7].

A. Reactive Safety Management Systems

Originally, ICAO safety management was limited to the reactive response to safety events that attempts to "do something to address the risk identified in an accident, incident, or safety concerning event, where mitigation happens but after it has already occurred." Reactive SMS, sometimes referred to as Safety I, provides for risk mitigation after the hazard has occurred with the objective to minimize the impact from safety critical situations. The approach has been successful in rapid response to undesired system states through reaction to safety data risks, threats, and hazards identified. However, reactive SMS provides learning based on only a small number of accidents and incidents that limits generalizing to normal everyday operations. SMS has evolved since early adoption of Annex 19 and the airline safety community recognized that a complementary proactive safety management approach was also needed.

B. Proactive Safety Management Systems

Whereas reactive SMS has an objective to mitigate safety events after the hazard is detected and the system is exposed to it, proactive SMS seeks to "provide mitigating action to something before an accident happens by evaluating all available safety operational data to identify risks from historical/latent data from past accidents or incidents or safety concerning events." What differentiates proactive SMS from reactive SMS is the use of aviation leading indicators to directly assess underlying factors and precursors to create a range of acceptable safety performance, and a framework for future risk exposure, mitigations, and safety assurance. The objective of proactive SMS, also referred to as Safety II, is to identify precursors and anomalies and potential causal factors, through data markers, system behaviors, passive sensors, and predictive human performance modeling that may lead to unsafe conditions and hazardous operations and attempt to preemptively stop the event progression of causal and contributory factors before a safety risk event occurs. Proactive safety is also referred to as productive safety reflecting learning from everyday operational successes, e.g., LOSA data show that adverse weather is a threat in almost 60% of normal flights [29]. Reactive and proactive safety management work collectively to quickly address previously undetected safety events, and continuously monitor and assess actionable safety data to identify root causes that may lead to more timely mitigation and/or prevention of specific risk event occurrence.

C. Predictive Safety Management Systems

Historical analyses evince that patterns of critical safety events, accident causation, and types of countermeasures have changed significantly over time and at present more random or unique factors generally contribute to accidents and incidents than in the past. Early safety management focused on prescriptive rules and regulations to manage more common system component failures. This has evolved into a more comprehensive safety management approach that addresses organizational factors, processes, and human performance across the four SMS pillars. Contemporary SMSs are now characterized by reactive and proactive safety management, which has improved data-informed approaches to systematically examine safety events and conditions more effectively in real-time, based on the actionable data identified. What is challenging today's SMS is the significant growth in data volume and, more importantly, the increasing uncertainty and complexity of etiological factors of modern safety events that can be identified and understood if the large volume of data can be properly analyzed. However, current SMS do not yet possess sufficient capability to continuously learn from the high volume of safety data. One significant factor limiting the full advantage of very large data sets is the lack of requisite advanced data analytical SFCs specifically designed and tailored for big data analytics. Big data analytics concern the use of advanced analytical techniques on large amounts of data to help uncover hidden patterns to unmask otherwise unidentified actionable data markers to predict potential latent safety risks for which traditional reactive and proactive approaches are less effective.

Predictive safety management attempts to identify all possible risks in different scenarios based on both observed but also hypothesized situations/circumstances to anticipate future risk controls, risk mitigation options, safety assurance, and organizational needs. Importantly, predictive SMS is complementary to, and not replacement for, both reactive and proactive SMS. Each is an important safety management approach, and all SMSs are intended to work collectively to enhance airline safety.

D. Predictive Safety Management — IASMS

Key to evolving towards commercial aviation predictive safety management will be safety intelligence that can integrate and fuse large disparate data from many diverse reporting systems and accessible database repositories. The IASMS is intended to provide prognostic and predictive safety intelligence through SFCs that can act "in-time" for reactive, proactive, and now predictive safety management. The challenge will be to leverage the many available safety occurrence reporting systems (e.g., airlines, FAA and other ANSPs, and other safety organizations), system monitored data (e.g., AIS, FDM, and A-CDM), and human monitored data (e.g., safety surveys, just culture, safety audits, and accident investigations). For example, the ASIAS program currently collects data from more than 100 sources with over 300 data feeds and manages tens of millions of records.

The growing prevalence of digital data systems, system-wide safety data networks, and accessible digital platforms have enabled the explosive growth in available safety data, which is projected to significantly increase by time when the 2045 Sky for All vision occurs. A consequence is the recognized need to manage this vast amount of information that is currently distributed across multiple systems. Some of these systems will need to be modified to provide compatibility and accessibility for data sharing that is requisite for true system-wide safety management. Increasingly, all aviation stakeholders (e.g., airlines, airports, FAA, and international organizations such as ICAO, EASA, IATA, and other ANSPs) are challenged to ensure that highly dispersed/scattered safety data are monitored and managed effectively despite often distributed siloed-source systems that have different data quality (e.g., 80% of data is estimated to be unstructured), formats, rules, taxonomies/ontologies, and other factors. Such management of data is critical to fully exploit and utilize them to identify safety risks and take predictive action to mitigate them.

Today, safety data collection, extraction, and interpretation are highly laborious and time-consuming processes that, in the highly dynamic and quickly changing environment of commercial aviation, is not efficient and is unwieldy. Safety data is projected to become unmanageable in the future based on forecasts of ever-increasing big data generation. The opportunity to take advantage of the richness of these data is very appealing, but if not addressed now, the effective use of these big data sets for data-driven and informed safety decision-making may become increasingly challenging. The potential for mass data fragmentation could lead unintentionally to new safety events being missed, and safety blind spots triggering unexpected safety critical events. To address this need, the international aviation community has called for the need to harmonize and standardize the management of safety information through the concept of "safety intelligence." For example, Flight Safety Foundation's "Global Safety Information Program" and ICAO's Safety Intelligence "Safety Information Monitoring System" and "Smart Sky" data intelligence and information system initiatives advocate for, among other needs, the use of novel advanced ML data analytics and mining methods, tools, techniques, and approaches. The IASMS ConOps is at a critical juncture for filling this need.

By effectively transforming their SMS to an IASMS, air carriers will be able to more effectively mine operational data and reduce iterative review cycle times between design and performance as shown in Figure 1. In-time decision making will be enabled by ML that will automatically detect and elevate critical risks for immediate attention. As decision makers gain confidence and trust in the IASMS, a subsequent concern may emerge relative to over-reliance on ML for safety critical decisions with drift toward always accepting recommended risk mitigations regardless of unique situational factors.

Safety intelligence is a growing theme among air carriers that are moving toward a more seamless, integrated global SMS. ICAO, as part of its SMS approach, emphasizes the global need for developing safety intelligence that leverages safety data and information to develop predictive and actionable insights leading to "in-time" data-driven decisions. Sharing safety information, including both Safety I and Safety II data, will be increasingly important to not only identifying emergent risks as aviation evolves internationally to different markets and missions with new entrants such as AAM, but to also inform new designs and approaches to optimize safety and performance. For example, mixed operations at and around airports are expected to grow as electric Vertical Take-Off and Landing (eVTOL) aircraft speed the local transport of passengers and cargo. All these operators will share in understanding operational risks and their mitigations.

Tools that help to establish safety intelligence, such as an IASMS-enabled safety dashboard that seeks to characterize system-wide risk in-time could provide a portal to advanced predictive analytics and improve knowledge acquisition and management. Domestic and international safety dashboards enabled by IASMS data services enhanced by learning from all operations offer the potential to provide in-time information important to manage operational safety risks and risk controls.

VII. Learning from All Operations

Goals of SMS include identification of hazards and proactive management of threats to an acceptable level, which over past years has led to development of new data programs, such as safety reporting systems and flight operational data monitoring, and numerous risk assessment methods. This traditional safety management approach, however, focuses principally on "absence of safety" rather than its presence. While it is important to continue to learn from what goes wrong, there has been a growing call to expand the types of safety data that should be collected and included to inform commercial aviation SMS to not only learn from "what goes wrong" but also to try to learn from "what goes right" to cultivate an organizational culture of continuous learning [30, 32]. In other words, data and analytics are needed to progress the understanding of "what goes right," such as in terms of capturing the human decisions and actions for ensuring and maintaining safe operations and trapping potential drift in operational practices away from nominal procedures and training.

To evolve SMS to an effective IASMS for commercial aviation, the IASMS ConOps provides a path that applies advances in data analytics and the inclusion of novel actionable data types to better aid aviation safety organizations to look more broadly at system safety. The continuous learning organization is predicated on data-informed safety intelligence that builds on IASMS in-time predictive data analytics to provide a more systematic and comprehensive learning-based approach. With IASMS, this "learning from all operations" viewpoint looks broadly across traditional but also new and underexploited data types, providing the overarching perspective for how organizations may maximize opportunities to "learn from safety" rather than merely "knowing about safety." This novel inspired way of system safety thinking reflects a shift in not only how we view safety data, but more fundamentally how we characterize safety generally.

Today's aviation safety organizations must continuously learn to cope with increasing and changing operational demands and conditions. Moreover, as we consider the future of aviation and how to achieve the visions safely, it is necessary but not adequate to learn only what not to do, but also to anticipate past mistakes and failures and act to avoid them. This is the hallmark of the predictive SMS. Although the traditional approach may provide some bulwark to minimize the recurrence of certain hazardous events, learning only from infrequently occurring safety events results in the organization learning only rarely. Learning only from mishaps does not enable an organization to take full advantage of all opportunities to address safety even though learning from all operations is not easily accomplished [30, 32].

To foster the continuous learning organization, it is essential that an IASMS capable of in-time and predictive (integrated with reactive and proactive) safety management also involves cardinal changes in the language of safety employed for a novel in-time predictive safety intelligence approach. The advantage is that this systematic transformation of SMS to IASMS builds in safety intelligence as part of the continuous learning organization. It is posited that this will better allow for learning about safety to enable the aviation SMS community to make data-informed adjustments to operations and safety policy and promotion in-time while informed by the SMS pillars of risk mitigation and safety assurance. In other words, it can enable transformation of all four SMS pillars to evolve to become an integrated IASMS capable of "in-time" reactive, proactive, and predictive safety intelligence that is fostered through an organizational culture of continuous safety learning. The IASMS can serve as the magnet for establishing a common vision for air carriers and the aviation community working toward a common goal of learning from all operations.

A. Data-Informed Decisions

The goal is for safety decision makers to make better decisions informed by data. SMSs provide a structure for the identification, collection, analysis, and dissemination of those data. Successful safety management depends (in part) on being aware of current performance, continually identifying opportunities for safety learning, establishing processes to evaluate safety performance and impacts of interventions, and communicating what is learned across all aspects of the SMS process. Because of the dynamic nature of operations and ever-expanding capabilities to collect and analyze both existing and novel types of safety-relevant data, the SMS process must also adapt, and these adaptations can impact all pillars of safety management. Consequently, these adaptations can enable an SMS that continually learns as reactive, proactive, and predictive safety intelligence grows.

The IASMS, therefore, can help organizations make data-informed safety adjustments without having to wait for something to go wrong or for a proactive action to save an operational situation to assure operational safety. As shown in Figure 5, most commercial operations end well with the vast majority being normal everyday operations falling along curves 1 and 2 [32]. However, most data analytical resources are put toward safety learning, focused on curves 3 and 4. The factors that precede both successes and failures can occur in much the same way. The delineation of these factors is made more challenging by the highly adaptive and resilient performance of human operators that can mask anomalies, which complicates their detection using a traditional safety lens.

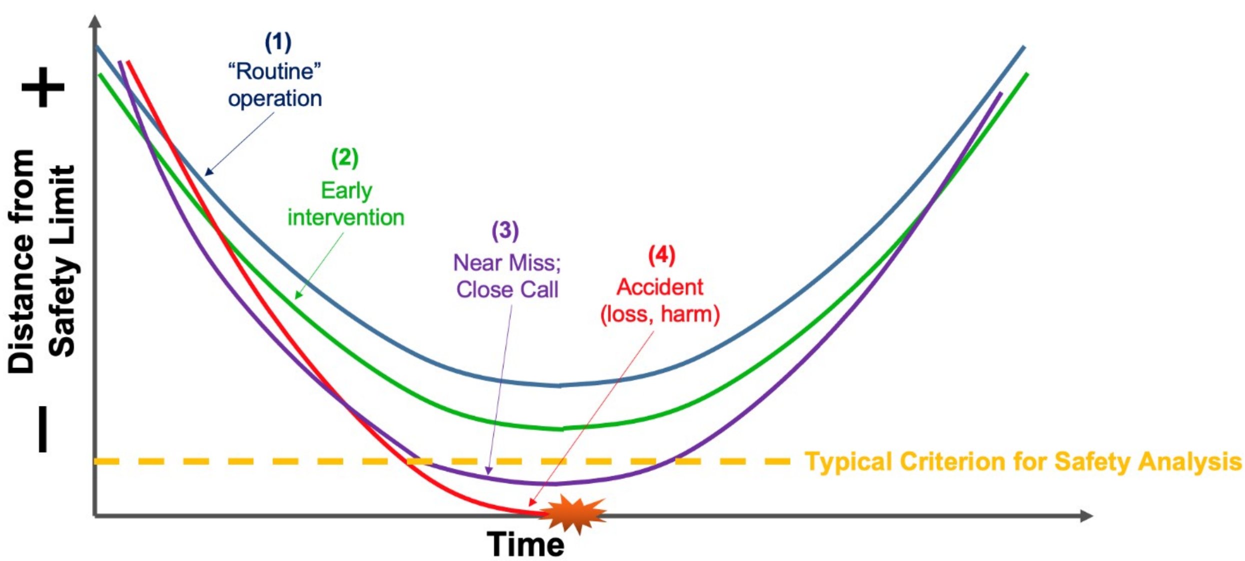

Fig. 5 Safety-Relevant Occurrence Types [32].

Changing how we define safety by expanding our understanding of what constitutes a safety-relevant issue can inform this learning. Through open- and closed-loop recursive feedback from in-time predictive safety intelligence, the IASMS can help to ensure the safety of operations as well as guide system safety design. One result of this paradigm shift in system safety is thinking in terms of "productive safety" and not limited to only "protective prescriptive safety." Productive safety springs from the concept of operational drift towards the safety boundary and countering that with the pull of safety culture for producing safety as part of operations, not just maintaining safety [33, 34]. This sea change in "learning from all operations" moves the state-of-the-art in ML data analytics to form the new state-of-the-art of an IASMS capable of in-time predictive safety intelligence for the continuous learning aviation safety organization.

B. Use of Data in Learning from All Operations

When organizational learning is systematically restricted or limited by focusing only on rare failure events, learning opportunities occur less often. Consequently, this low frequency of occurrence leads to an increased possibility of drawing misleading, even dangerous, conclusions by relying on a non-representative sample of how humans perform and contribute to safety. The absence of safety evidence (data) does not equate to evidence of the absence, or presence, of safety [30, 32].

Changes in how we define and think about safety can highlight new opportunities for collection and analysis of novel and currently unexploited safety-relevant data. Developing an integrated safety picture to better inform safety-related decision making and policies depends upon identifying, collecting, and interpreting behaviors that helps to ensure to safety of operations in addition to safety-reducing behaviors. The traditional safety lens approach does not currently examine such types of data although there is a growing recognition in the airline SMS community of the potential value of looking at such underexploited data and exploring other yet unidentified productive safety data types and sources.

Examining unexploited safety-relevant data presents an opportunity to integrate such data types into safety management systems, including addressing the challenges in collecting and analyzing the largely unexploited data on desired, safety-producing operator behaviors and looking at how to fuse these data with more traditional data sources. This opportunity would provide benefit to growing safety intelligence and facilitate a culture of continuous organizational learning. Changes in how we define and think about safety can highlight new methods for collection and analysis of safety-relevant data with the goals to minimize opportunities for undesired operational states and maximize opportunities for desired states.

While learning from frequent successes has the advantages of increasing sample rate, granularity of operational data, and timeliness of safety learning, it poses important research issues about determining what data to capture, how to analyze and manage this potentially massive expansion of safety data, what data analytics methods work best on these novel data types, and how to translate learned insights into policy and design decisions. The technical challenge is to look deeply and systematically across the distributional pattern of the data as opposed to individual safety events as is more common with contemporary airline SMS. This approach is well-suited for ML data analytics techniques and methods. ML provides a more systematic capability to look not just at outcomes but also processes latent to today's SMS that are critical to better inform design, implementation, and practice of IASMS for commercial aviation and enable in-time and predictive safety management in the continuous learning safety organization.

VIII. Human-System Integration

Systems have become more autonomous, and proposed calls to supplant human expertise with increasingly automated systems take different forms under the rubrics of semi-autonomous and fully autonomous systems. Design of these systems is expected to add more capabilities and increase complexity including emergence of novel opportunities for new types of human-system failures. Historical evidence has shown the impacts that lack of early and careful considerations of the human role when interacting with highly complex systems has on design success and ultimately its safe use. Furthermore, the commonly reported 80% of aviation accidents caused by humans is often reported incorrectly in terms of actual data and can be misleading relative to the specific human contribution to aviation safety [35, 36]. It is understood that humans provide resilience to systems in the event of unexpected off-nominal situations. Human operators routinely manage off-nominal situations every day and respond to these events without compromise of safety [30]. Unfortunately, such instances are rarely documented and tracked, thereby limiting opportunities for organizational continuous learning. In addition, early studies suggest that the introduction of semi-autonomous systems has the potential to reduce operator engagement, possibly leading to increased loss of situation awareness [37].

Systems for today's commercial aviation SMS are often designed to require highly specialized and trained personnel or need significant accommodation for use across a wide population of human capabilities that need to be considered. The eventual implementation and use of IASMS will show these challenges may be more acute given the use of ML that can be difficult for even experts to decipher and understand how these algorithms classify very large data sets. With the human analyst in the safety critical decision loop, there will be a for need specialized training with continuous learning.

To help ensure the IASMS addresses the above design considerations and potential challenges, Human-System Integration (HSI) efforts will need to focus on early life-cycle design requirements as informed from MBSE activities [31]. HSI has been defined as “a required interdisciplinary integration of the human as an element of a system to ensure that the human and software/hardware components cooperate, coordinate, and communicate effectively to perform a specific function or mission successfully [38].” As a discipline, IHSI is a natural evolution of Human Factors Engineering (HFE), to include Human-Computer Interaction (HCI) through application of many decades of user interface design and human-centered systems engineering. An HSI approach that addresses the entire NPR 7120.5 system life cycle could contribute to development of an IASMS Human Systems Integration Plan (HSIP) [39]. The HSIP could include development of a set of human interfaces and management of information (HIMI) design recommendations for planned IASMS prototype leading to development of requirements necessary for full deployment of commercial aviation IASMS by targeted future vision timelines.

C. Human Interfaces and Management of Information

Design of HIMI will be critical to successful deployment of IASMS. Management of safety information may be a key enabling portal through which humans can team with increasingly autonomous systems for safety assurance and in-time risk management. For example, as in-time system-wide safety assurance data becomes increasingly available, a challenge posed is how these data support humans through trustworthy decision support in the context of a substantially increased number of available data streams, volume of data, rate of information, variation in data quality, validation and verification, edge computing, and more complex and nuanced risk factors that may impact operational safety. Today, safety managers and review boards often must sequentially review these siloed, stove-piped data sets. Transitions to in-time data analytics will require fused data to identify known precursors, anomalies, and trends as well as emergent risks more quickly and effectively.

As automated systems increasingly make use of ML to handle big data, the underlying algorithms will evolve in sophistication. This may exceed what humans are able to understand if HIMI is not considered early in the system design lifecycle of IASMS development. Research has shown the difficulties experts have in understanding the non-deterministic “black box” methods of neural networks and other advanced data analytical capabilities. Human decision makers will be trained to trust a system, but in a manner that may exclude or limit understanding of the underlying algorithms making HIMI a critical consideration for IASMS design. The human-autonomy teaming (HAT) design approach is also expected to be a cornerstone for IASMS design guidance that supports operator information requirements. HIMI will shape the design for these information requirements, and training and procedures will help to avoid well-documented potential for poor use, and/or misuse, disuse, and abuse observed today of human-system interactions using advanced automation/autonomous technologies. New and different HIMI standards and guidelines will need to be updated to support the information requirements of an IASMS [40, 41].

As the aviation system and in-time system-wide safety assurance methods become more capable as well as complex, some key questions about HIMI include how should information be scaled for display and how should the human operator drill down for more details? How should safety dashboards be tailored for information requirements of different users? How should time critical information be pushed to the display, even to interrupt whatever was being displayed at that time? How much training and education should be required relative to the level of understanding needed of the underlying algorithms? How does the cognitive state of the human alter engagement with systems? IASMS addresses these and other key concerns in a manner that leverages best practices where available. The design process may identify opportunities for new types of interactions and highlight knowledge gaps for a more comprehensive design approach for IASMS. HIMI design recommendations are needed to technically guide development of IASMS prototypes. Additionally, a more comprehensive HSIP for commercial aviation IASMS could guide and inform needed HSI research and formal specification of IASMS HSI design requirements.

D. System-Wide IASMS

Safety intelligence is a fast-growing theme among air carriers that are moving toward a more seamless, integrated global SMS, and multiple organizations have called for efforts toward predictive SMS and ML-based safety intelligence. Developing accessible digital information platforms and IASMS dashboards to share safety information will become increasingly important for identifying emergent risks for commercial aviation operators. These platforms could be extensible to other emerging concepts of operation, such as AAM, Class E long-duration fleet operation, and commercial space launch and reentry that is spreading internationally to different markets and missions.

IASMS dashboards are intended to provide a portal to predictive analytics and improve knowledge consolidation and management. Multiple domestic and international dashboards are envisioned to provide in-time information important to operational risk assessment and risk controls. Development of the IASMS ConOps involves collaboration with partners, external stakeholders, and the SMS community to develop a roadmap toward a system-wide, IASMS capability intended for all airspace users. Prior research on predictive analytics focused on building an initial, limited data-sourced dashboard developed in collaboration with a U.S. major airline partner [19]. The IASMS ConOps substantially extends this foundational research by defining multivariate data analysis and decision SFCs for predictive data analytics in support of continuous learning organization safety management. New intersections can be identified through interchanges with other research projects and leading international SMS organizations on safety intelligence. These collaborations can address information access, digital data platforms, and system-wide IASMS SFCs. As an example of demonstrated need for predictive SMS, the FAA ASIAS ConOps 3.0 identified future changes required including use of advanced data analytics that leverage data fusion capabilities developed in ASIAS 2.0, along with improved collaborative activities and improved responsiveness for requested information and studies.

IX. Opportunities to Demonstrate IASMS with Air Carriers

The integrated IASMS capability addresses the need for more advanced methods and tools critical to enable efficient and deeper analyses of safety data. Use of predictive analytics goes beyond how air carriers analyze data in today's operations. Integration of data mining tools providing advanced predictive analytics could be demonstrated for assessing convergence across multiple data sources to identify operationally significant anomalies, precursors, and trends involving system and human behaviors as well as new emergent risks. IASMS SFCs use these different data sources for monitoring, assessment, and mitigation of operational risks. The design and prototyping of a data decision dashboard would address cognitive requirements for in-time monitoring and identification of nominal and off-nominal system and human performance.

There will be opportunities for assessing the benefits and limitations with the business case for commercial air carriers. These targeted demonstrations are important for identifying and prioritizing capabilities and design requirements for advanced predictive analytics and the prototype data decision dashboard. At a strategic level, research must investigate how to integrate and fuse targeted data streams that offer the highest potential to enable effective predictive analytics capable of quickly identifying and characterizing known and emergent risks. Further development and refinement are also needed to address and reduce missed, overlooked, or masked risks in predictive analytics output, and to integrate the safety dashboard as an efficient and effective tool for the executive authority agent in the system. Future research needs include the following considerations:

1) An integrated risk-based decision fusion assessment and mitigation capability through identified representative commercial airline operations use cases
2) Anomaly detection, precursor identification, identification of human contributions to safety, and prediction algorithms using simple to increasingly complex data sources
3) Different types of data to identify unusual events and their nature (e.g., statistical anomaly, operationally significant anomaly, recovery action)
4) Prototype system for visualizing results of the risk assessment and mitigation decision fusing capability combined with human input and feedback
5) Prototype system that describes the state of the aviation system and human cognitive state described by current data sets, and how far the system is from known anomalies or unknown anomalies (i.e., how close in time and circumstances the system is to show anomalous operations)
6) Initial recommendations for interoperable IASMS system requirements and guidelines through use case of commercial aviation operations within a shared airspace

X. Change Management in the New Vision

Change management is the collective term for concepts, methods, and approaches for the coordination of periods of system transitions and associated processes governing oversight, facilitation, and execution of changes, the management of emergent complexities, and the diverse set of change drivers for effectual change in the NAS through envisioned, intended outcomes and mitigation of unintended outcomes. The creation and evolution of the IASMS will be subject to managing architecture changes as separate implementation types for commercial carriers and other operators, such as small urban UAS operations and disaster management, that in the future will merge into the application appropriate to a single, more seamless aviation system. NASA is developing a "Sky for All" vision to enable a safe, resilient, sustainable, and adaptable future aviation system through innovations realized by advanced and continually emerging capabilities for agile, optimizable, scalable, and increasingly diverse and equitable operations in a shared negotiated airspace [1]. The vision reimagines the future of aviation for a mid-century targeted date of 2045 that recognizes the transformation required to reshape the future aviation system through bold, new approaches to meet the demands of new concepts of operations, increased volume of air traffic, novel and emerging vehicles, and potential envisioned complexities and uncertainties. Mega-drivers influencing the

NASA vision include diversity, dynamic convolutions, and increasing complexity of vehicles, operations, performance, and missions; increased density and volume of operations; and highly integrated heterogenous collaborative and more autonomous airspace. The NASA Sky for All vision will necessitate and introduce new SFCs to include: (a) augmented operations via intelligent/adaptive automation and autonomy; (b) cooperative and coordinated digital flights; (c) transformed digital airspace; (d) accessible integrated digital platforms; (e) micro-services for flight operations; and (f) anywhere, anytime all-weather operations. Key to achieving the vision will be considerations on how to do this safely to include establishment of change management processes and safeguards.

The FAA, as part of its Next Generation Air Transportation System (NextGen), continues to envision transformation of the NAS to a system very different from today's NAS. The future NAS entails continuous and ubiquitous data fusion and exchange, increasing use of ML, expanded autonomous aircraft operations, and new integral human-machine teaming all in the same volume of airspace [2]. This future NAS will also involve changes associated with UAS traffic management (UTM) to address unique challenges such as airspace design and vehicle operations [42]. Another type of operation that will need to be included in a future IASMS is Upper Class E airspace defined in the FAA ConOps for Upper Class E traffic management as 60,000 feet and above and represents increased operational complexity [43]. Upper E airspace includes supersonic and suborbital flights, such as the Virgin Galactic flight that reached 282,000 feet. Lastly, change management will be required to accommodate the increasing number of space launch and reentry operations. The above examples represent just a few of the potential number of changes that are possible for the future global aviation system, underscoring the importance of change management.

XI. Conclusions

In sum, transforming the SMS for Part 121 commercial air carriers with evolution of the IASMS as part of the future visions proposed for aviation requires significant changes and challenges for in-time safety. An incremental path using building blocks will facilitate and speed refinements toward SMS responsive to the new envisioned concepts of operations and technological innovations expected. IASMS will advance aviation safety across the four pillars of the ICAO-defined SMS. Predictive analytics will advance the state-of-the-art capabilities in detecting, assessing, and mitigating anomalies, precursors, and trends for air carriers as well as identifying emergent risks exposed by the transformation of the NAS. Safety intelligence will expand the data available and offer insight to new approaches for safety enhancements and safety promotion to mitigate risk, with more seamless "in-time" integration across the policy, promotion, risk management, and safety assurance of the SMS pillars.

Today's rapidly evolving aviation markets and envisioned new concepts of operations pose new critical safety risks with novel types of vehicles (e.g., eVTOL) having frequent flights each day, with typically short durations, within proximity of one another carrying people and cargo, and in more congested and operationally complex airspace. To move toward this vision, there is a need for concomitant changes to how safety is assured by increasing the fusion and integration of "in-time" operational data displayed while still managed by human decision makers. A key attribute of an IASMS is that it supports the human to quickly manage known or predicted operational risks through highly automated systems that integrate SFCs across operator and federated architectures. These on-board, ground-based, and cloud digital information systems collect, fuse, model, and distribute data that are used by IASMS subsystems. These safety subsystems monitor and assess the data for detected risk with risk mitigations executed in-time. Identifying and mitigating emergent risks necessitate innovative solutions involving advanced data analytics including ML that integrate proactive methods, built on precedent and predictive methods that intercede to disrupt the projected time series of causal and contributing factors. Lastly, an IASMS will quickly inform system design as emergent hazards are identified so that effective risk controls are developed

The IASMS provides risk management and safety assurance utilizing system-wide data to provide alerting and mitigation strategies much more effective and responsive to resolving known and unknown risks than possible with today's SMS. Emerging technologies and capabilities are enabling new ways for humans to interact with data that have not been possible before. To achieve the IASMS objectives, the human's roles and responsibilities are envisioned to transform in pace with the equally transformative changes required to achieve the aviation future vision. A critical challenge for moving IASMS from concept to actual practice, as part of commercial aviation SMS implementation, necessitates considering the proper human role and responsibilities in these systems. These considerations include remedying observed limitations found with SMS today as well as accounting for changes associated with the NASA Sky for All and other future organizational visions.

Importantly, the human is still expected to have critical, safety operational, over-the-loop roles of some nature as well as data analyst roles in future commercial aviation SMS. Research is needed to tackle important questions including assessing the necessary and proper role of humans as part of an IASMS. Considerations include use of system modeling and early definition of HSI requirements for the IASMS to better understand and design for human performance and HIMI. This human-centered design of IASMS defines the data portals through which humans will interact and team with ML and other data analytical SFCs as part of the joint cognitive decision-making processes required to maintain safety under increasing operational conditions of safety uncertainty. As aviation embraces new advances and technological innovation to address mobility and sustainability needs, the IASMS provides a keystone to ensuring the future global air transportation system is a revolutionary and safe "Sky for All."

Acknowledgments

The authors extend their appreciation to Ms. Laura Bass (Analytical Mechanics Associates, Inc.) for her important and numerous contributions in the development of this paper.

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