Information Fusion for National Airspace System Prognostics: A NASA ULI Project

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ABSTRACT

Expanding Prognostics and Health Management (PHM) from an equipment-centric view to complex large-scale engineering systems is a challenging problem. One example for a large engineering system is the next generation national airspace system (NAS), which is a fully coupled cyber-physical-human system. This paper presents an overview of a NASA University Leadership Initiative (ULI) project which aims to address the safety needs and their technology solutions for future NAS. The ULI is a 5-year collaborative project in which researchers from several universities and commercial entities work together to advance real-time airspace safety concepts. The underlying premise is that it is imperative to be able to assess and predict the evolution of the airspace's safety state. Towards that end the work envisions to address the following issues: modeling of the airspace using both data-driven and physics-based approaches; quantifying and managing uncertainty; advancing prognostics and information fusion algorithms; and understanding and modeling human computer interface. A comprehensive simulation environment is being built that allows for assessment of performance and verification and validation. The paper discusses the various activities and places them into the context of overall NAS safety.

1. BACKGROUND AND OVERVIEW

The next generation (NextGen) national air transportation system will include a number of changes. In particular, a multitude of new and existing aviation data sources are expected to become available, such as from Automatic Dependent Surveillance - Contract (ADS-C) and Automatic Dependent Surveillance – Broadcast(ADS-B) (ADS-B) surveillance systems-based operations (McCallie, Butts et al. 2011), voice and data communications, weather forecasting, and aircraft health data. However, several critical challenges exist for systematic integration and interpretation of the enormous amounts of information associated with national airspace systems (NAS). For example, it is anticipated that the myriad of information offered by various data sources in the future will require appropriate representation and fusion methodologies. Furthermore, a large amount of uncertainty is associated with this information arising from various sources such as aeronautical instrumentation, environment, intrinsic variabilities, and limited knowledge of human-system integration on safety (Lintner, Smith et al. 2008). Complex system safety modeling of multiple failure modes (e.g., loss of separation, mechanical and electrical sub-system failure, miscommunications, human-automation errors, and weather-related hazards) with largely unknown uncertainties is extremely valuable for the safe transition of the present NAS to NextGen concept of operations. In addition, as the NAS adopts new NextGen technologies to enhance its capacity, efficiency, and uses, maintaining a safe system has created the need for real-time responses for risk mitigation. A system-wide prognostics framework equipped with rigorous verification and validation methodologies for proactive health management of evolving NextGen NAS, hence, is of both technical and practical urgency.

The objectives of the study are to develop an integrated real-time system-wide information fusion methodology for prognostics and safety assurance of the NAS. Various sources of uncertainties and their coupling effects are systematically investigated for accurate failure and risk assessment of the extremely large-scale, complex NAS. A community-based collaborative simulation platform will be developed for continued sustainable prognostics technology evolution for the NAS safety research

2. NASA STRATEGIC THRUSTS

NASA's Aeronautics Mission Directorate has defined a set of Strategic Thrusts (NASA 2017) that are setting the agency's research agenda to global trends affecting aviation. These thrusts encompass a broad range of technologies that are meant to meet future needs of the aviation community, the nation, and the world for safe, efficient, flexible, and environmentally sustainable air transportation.

2.1. Real-Time System Wide Safety Assurance

One of these strategic thrusts is Real-Time System Wide Safety Assurance (NASA, 2017). Continuous efforts to reduce risk in commercial aviation over the last few decades have made it the safest mode of transportation. Yet, as aviation adopts new technologies to enhance the capacity, efficiency, and uses of the NAS, maintaining a safe system will require detection and timely mitigation of safety issues as they emerge and before they become hazards. Needed are capabilities to ensure safe operations in a more complex airspace through proactive detection, prognosis, and resolution of emergent threats to system-wide safety. Envisioned is a safety net that utilizes system-wide data to provide alerting and mitigation strategies in real-time to address emerging risks.

2.2. ULI Vision

ULI is a project initiative that was meant to engage Aeronautics Research Mission Directorate (ARMD) and the academic community in a new type of interaction where universities take the lead, build their own teams, and set their own research path. ULI seeks new, innovative ideas from university-led teams to support the NASA ARMD research portfolio and the U.S. aviation community. To that end, university teams are being challenged to address unique research questions associated with ARMD strategic thrusts (NASA 2017), defining interdisciplinary solutions, establishing peer review mechanisms, and applying innovative teaming strategies to strengthen their research impact. In order to transition their research, the projects have been challenged to actively explore transition opportunities and pursue follow-on funding from stakeholders and industrial partners during the course of their award. This paper describes the efforts that are being undertaken for the ULI project awarded under the strategic thrust Real-Time System-Wide Safety Assurance.

3. METHODOLOGY

A general methodology for PHM of NAS involves close interactions among several distinct disciplines. Central to the large-scale multi-source information fusion supported via several key building blocks is the generalized Bayesian-Entropy Network (BEN). A schematic illustration of the overall framework is shown in Figure 1. Each component is briefly discussed below.

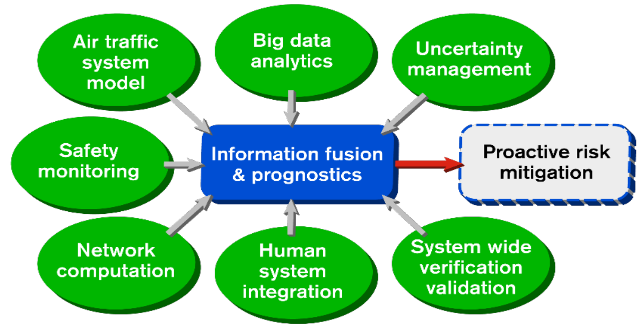


Figure 1. Schematic illustration of information fusion methodology for prognostics

3.1. System-wide air traffic modeling and failure simulation

A domain knowledge-based air-ground traffic simulation framework is required for prognostics and risk analysis (Figure 1.). The current study advances a computational framework in which factors impacting the safety of national airspace operations can be modeled and analyzed to assess emerging safety issues.

This framework is termed as the National Airspace Traffic-Prediction System (NATS) throughout this paper. NATS is implemented as a server-client software package that incorporates realistic models of three major subsystems: Equipment, Entities and Environment. (1) The Equipment category includes aircraft, flight-deck automation equipment, ground vehicles, and surveillance and communication systems. (2) The Entities category includes error models of all human operators involved in NAS operations such as pilots, air traffic controllers and ground vehicle operators. (3) The Environment subsystem consists of airports with ramp, taxiways and runways, en-route and terminal area flight operations procedures, terrain, and weather. Any other subsystem models to be considered in the analysis can be modeled by the analyst and integrated with NATS under one of these three categories.

The development of this simulation framework is based on NASA tools (ACES and FACET) and OSI codes (CARPAT) that use filed flight plans and the instantaneous aircraft states in the NAS for forecasting traffic flow evolution. The impact of traffic management initiatives caused by weather and other factors affecting traffic flow will also be included in future work. This part reflects the information sources from existing understanding of the complex NAS system.

A block diagram of the system-wide air traffic modeling and failure simulation flow chart is shown in Figure 2. The simulation system is built around NASA air traffic simulation tools such as FACET (Bilmoria, Banavar et al. 2000), ACES (George, Satapathy et al. 2011), SOSS (Wood, Kistler et al. 2009, Windhorst 2012) and ATG (Jung, Hoang et al. 2011). Hardware-accelerated air traffic simulation software such as CARPAT (Tandale and Menon 2008, Tandale, Wiraatmadja et al. 2011) may be included to address the needs for iterative simulations such as Monte-Carlo simulations. Surface traffic simulation tools such as ATG is being incorporated to allow the analysis of system safety on ramp, taxiways and runways. Aircraft databases such as BADA (Nuic 2010) are being used to enable the trajectory simulation of every operational aircraft currently operating in the NAS. Historic flight plans and weather data from NOAA (Tandale and Menon 2008, Tandale, Wiraatmadja et al. 2011) are being provided for simulation. Evolving NextGen automation tools such as new controller decision-support systems, airborne self-separation algorithms, precision navigation systems, and trajectory-based operational capabilities is being included to enable analysis of these systems on overall NAS safety.

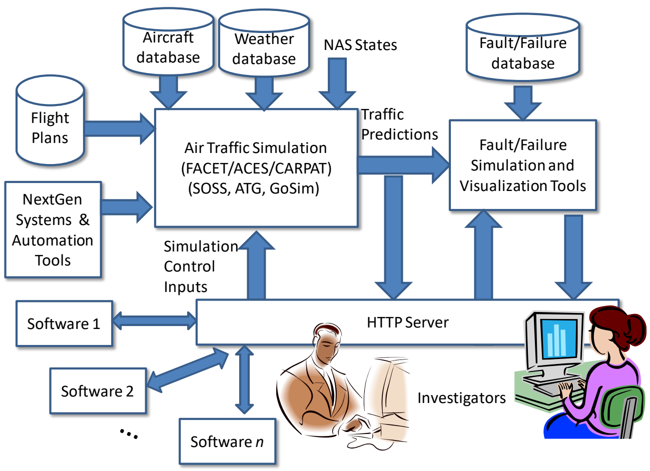


Figure 2. Schematic Illustration of NAS Air Traffic Prediction and fault/Failure Simulation

Next, the domain-knowledge traffic model is being transformed into a mathematical dynamic formulation (e.g., state-space equations) to facilitate the future prediction and information fusion. In this study, the concept of physics-based learning is investigated and a new prognostics algorithm for aircraft dynamics simulation is developed. Physics-based learning is a hybrid approach that utilizes both the data-driven learning and the underlying physics of dynamical systems to achieve more efficient learning and prediction. Specifically, the underlying physics of the dynamical system is integrated into the learning models such as RNNs to provide additional constraints for the learning and prediction of behavior of dynamical systems. By doing so, the physics-based learning method is able to greatly reduce the training costs associated with the purely data-driven approach. The trained model can serve as surrogate models for aircraft dynamical systems and thus reduce the high computation costs of solving the system numerically. Furthermore, the integration of the physics enhances the extrapolation capability of the trained model. This is considered as a desirable feature since the long-term responses of dynamical systems under arbitrary inputs are often of interest. Recently, a physics-aware RNN architecture known as the deep residual RNN (DR-RNN) was introduced (Kani and Elsheikh 2017). The DR-RNN formulates an iterative scheme to minimize the residual function that is computed using the underlying physics of the dynamical system. In this study, the DR-RNN is adopted to handle learning of aircraft dynamics.

Another major component is the big data analytics module that is used to develop metrics-based safety measures that can be used for prognostics. Multiple data sets consisting of different types of historical aviation information are mined, including NTSB Aviation Accident Database & Synopses, FAA Aviation Safety Information Analysis and Sharing (ASIAS) Source Databases, Automatic Terminal Information Service (ATIS), to name a few. The goal is to build predictive models that take as input multi-sourced data, or multi-view data, and output the predictions regarding various types of fault/failure modes, such as wake turbulence related accidents, pilot errors, mechanical errors, and sabotage. A heterogeneous learning framework for scalable and real-time failure and risk identification from multi-modality input data consists of the following two key components:

a) Multi-view rare category analysis for detecting fault and failures. A single view only corresponds to the features from one information source (one view), e.g., text information from ATIS. The goal is to identify fault/failure modes (which are rare compared with the normal working modes) by integrating the weak signals of such rare events from all the views. As a pre-processing step, the data are being converted from all the information sources into numerical forms. For example, to process the text information from ATIS, one first builds a vocabulary consisting of key words commonly used in aviation and airport environments. Each piece of recorded information is mapped into a numerical vector using, e.g., the bag-of-word model (Schütze 2008), or the Word2Vec model (Goldberg and Levy 2014). Then based on these numerical features from multiple views, novel multi-view rare category analysis algorithms are designed to output a list of events ranked in descending order of their probabilities of fault and failures. These algorithms are based on the alternating direction method of multipliers (ADMM) (Boyd, Parikh et al. 2011). End users of these algorithms can look through the top ranked events, and identify them as positive with a specific fault/failure mode or negative (normal). Such feedback is used as auxiliary label information (Jansen and McNeese 2005) to improve the performance of the multi-view rare category analysis algorithms.

b) Multi-label learning for multiple fault/failure types. Given multiple types of fault/failure available in historical data, a natural idea is to construct separable models from each type independently. However, given the relatedness of different types of fault/failure, sometimes due to the co-existence of multiple causes, discarding the relationship among the different types might be sub-optimal (Gibaja and Ventura 2015). For example, a fault/failure might be caused by both pilot error and wake turbulence. To this end, a multi-label learning algorithm is used to simultaneously build models for multiple fault/failure types. The key idea is to form optimization problems where the objective function takes into consideration both prediction performance as well as relatedness measure in terms of various matrix norms (Yang, Yang et al. 2016) (e.g., the L2_1 norm). Such optimization problems can be solved using e.g., the randomized block coordinate descent algorithm (Richtárik and Takáč 2014). Based on the fusion of domain-knowledge and data analytics, the "risk" of the complex NAS system can be rigorously evaluated.

3.2. Multi-modality safety monitoring

PHM of NAS requires accurate and real-time state awareness and this is achieved by multimodality safety monitoring (Figure 1). For example, vehicle level flight information can be used to obtain engine status data (e.g., temperature and speed) which can extract their features to indicate health and fault states (see Figure 3). Once the data are obtained, advanced data analysis is used for data reduction and classification. The current study focuses on a robust real-time aircraft health monitoring framework using a machine learning based approach, specifically the multivariate Gaussian mixture model (mGMM), for the detection of in-air operational anomalies of an aircraft system. Sensor fusion and noise filtering algorithms have also been adopted to reduce dimensionality of the feature space while avoiding the elimination of useful information from the original flight data. Random noise in each feature, induced by the aircraft sensors and data acquisition system, is filtered out using a weighted averaging window while maintaining inherent variances. The filtered dataset is then fused according to the underlying physics of each sensed feature to reduce redundant features and subsequently trained using the mGMM. The methodology allows monitoring the behavior of each feature as well as correlations between features, significantly improving detection sensitivity. The high computational efficiency of this approach permits real-time monitoring of an aircraft system.

Beyond vehicle level monitoring, ground and in-air surveillance monitoring is integrated within the prognostics framework to automatically assess conditions of aircrafts and various spaces relevant to air traffic management (e.g., runway, airspace), and detect anomalous ground and in-air events and activities across those spaces (e.g., a pilot deviated from a rule of ATC instruction). The goal is to provide spatiotemporal details that depict the interactions between aircrafts, natural or built environments, resources, equipment, and humans involved in various in-air and ground operations. Existing air traffic surveillance technology, such as ADS-B, can automatically report aircraft position, altitude, speed, elements of navigational intent and meteorological data (McCallie, Butts et al. 2011), but needs tedious manual/semi-manual operation to extract spatiotemporal relationships. Real-time computer vision, spatiotemporal pattern analysis, and spatiotemporal reasoning techniques is examined with the goal to automate the recognition of objects and the detection of anomalous objects from imageries.

Here, object recognition algorithms are being developed that utilize both visual and spatial features of objects and spatiotemporal relationships between objects, such as aircrafts, human individuals, runways, airport facilities, and equipment and environmental objects from large amounts of imagery data (Tang, Chen et al. 2016). Specifically, a Conditional Random Field (CRF)-based method is used for reducing the search space of objects to match the properties and likely spatial relationships with nearby objects (e.g., runways should be below and parallel to the departing aircrafts) (Xiong and Huber 2010). A deep learning algorithm can mine such spatial relationships from large number of imageries and then obtain hierarchical object-relationship knowledge for supporting CRF-based recognition (Lee, Grosse et al. 2009). The CRF-based approach uses spatial relationships between objects for narrowing down the search space of the recognition problem, and also utilize the temporal relationships captured in videos in order to eliminate mismatches.

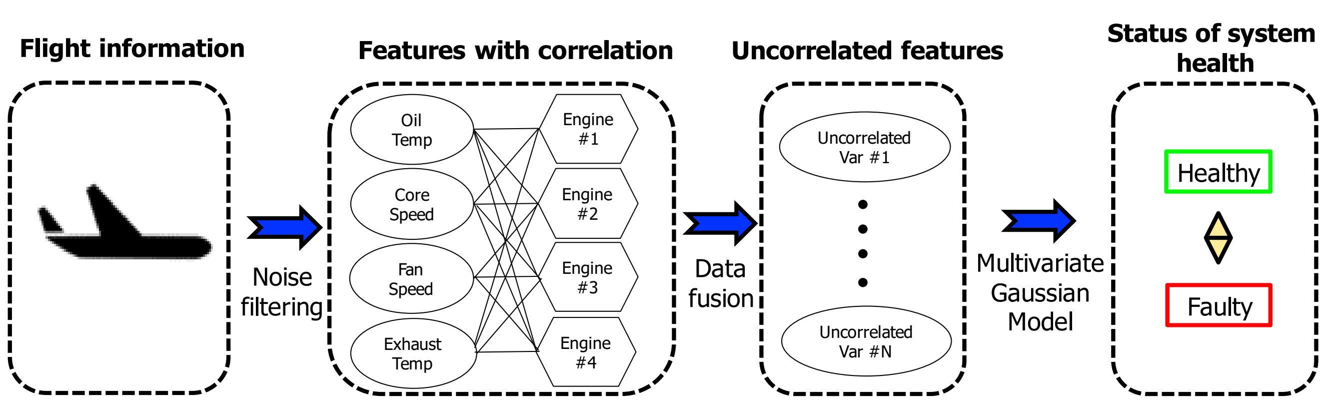


Figure 3. Schematic illustration of vehicle level healthy state identification

In addition, the approach utilizes the contextual features of objects to significantly improve reliability and efficiency of tracking objects that have complex motions in low-contrast videos (Li, Wu et al. 2014, Sun, Zhang et al. 2016).

3.3. Human system integration

One of the most important factors for NAS safety is human performance. A holistic prognostic health management approach must include the information and models to evaluate the impact of human behavior. The BEN requires that the sources of information provided as input to the BEN consider the decision making of air traffic managers. Factors that ATMs currently use to make their decisions and how they weight and combine factors in their decisions are being explored through text analysis of historical data and records, and c) elicitation of the knowledge of expert air traffic managers (ATMs Given the rich array of information that could be presented to the controller and pilot, it is essential that information needs are identified, classified, and prioritized., ATMs rely on many different sources of data that include visual information in flight strips and radar displays, visual and auditory alerts, weather information and runway information, and communications with pilots and other controllers (Wickens, Mavor et al. 1997). Archival data from these types of analyses are being collected and aggregated in an inventory.

Unstructured historical data and records (e.g., computer logs, natural language reports about aircraft inspection results, flight delay records, historical performance records of pilots and aircrafts) can be mined to extract knowledge about information needed by ATMs in certain scenarios of air traffic management, aircraft inspection, runway and facility inspection, and airport pedestrian traffic analysis and evacuation. Since a manual analysis of such historical data is tedious and error prone, a semantic data model is being developed that can be used to represent the information commonly available in historical documents, such as inspection records of facilities, technical specifications, runway intrusion records, and flight delay records. Such a semantic data model, as shown in the literature about document analytics for improving designs of various engineering systems (e.g., buildings, software systems, manufacturing systems) (Gruber 1995, Zhang and El-Gohary 2013), is the type of information representation used by text mining methods and algorithms to automatically extract operational requirements from technical documents specifying tasks such as how to ensure safe and efficient operation of aircrafts, runways, airports in various weather conditions across multiple cities.

Finally, knowledge elicitation techniques including interviews and conceptual scaling methods can be conducted with experienced ATMs to identify information requirements of the system (Cooke 1994, Cooke, Neville et al. 1996, Cooke 1999). The goal is to identify the types of information used by ATMs to make decisions, the prioritization of different data sources, and rules for combining this information (Schvaneveldt, Beringer et al. 2001). The knowledge elicitation methods includes structured interviews and Pathfinder Network Scaling (Schvaneveldt 1990). Challenges associated with knowledge elicitation revolve around the elicitation of knowledge that may be difficult, especially for the most experienced ATMs, to verbalize. Techniques such as the critical decision method (Klein, Calderwood et al. 1989) are used in which the ATM recounts an important event from the past and can be questioned on the events surrounding a particular decision.

Human-in-the-loop simulation (through ASU's Air Traffic Control (ATC) simulation capabilities) is used to better understand the situation and process factors that relate to ATM performance. There are many factors relevant to human performance (e.g., situation awareness, workload, fatigue), which have been measured subjectively. These factors can also be detected by more rigorous methods in a simulation environment (Yoo, Lee et al. 2015). Simulators are equipped with measures of individual, team, and system performance, as well as process, including video records, communications measures, and tests of situation awareness. Participants from ASU's aviation programs are asked to participate as ATMs and pilots in these several experimental exercises. Scenarios are being developed that varies in complexity and task load to provide representative data on human performance. Individual ATM and team performance is measured using outcome-based metrics in the simulation environment such as mean separation of aircraft. Other situation and process factors is also measured to include situation awareness, workload, team process, and video and communication data (see Figure 4). Situation awareness can be assessed at the individual and team level by injecting faults into the scenario and tracking the team's ability to respond to them (Endsley and Garland 2000, Gorman, Cooke et al. 2006).

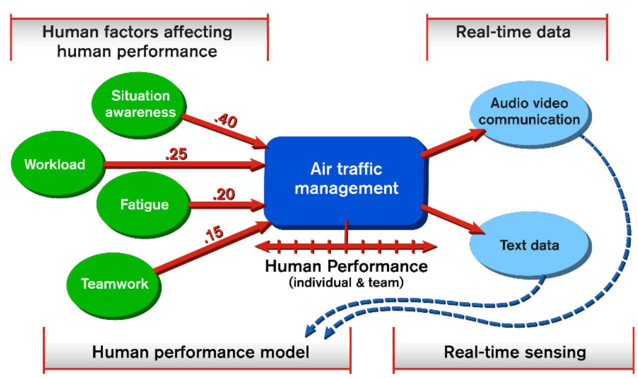


Figure 4. Schematic illustration of human factor modeling approach

Multiple types of metrics can be used to indicate the human performance. Previous studies have examined the feasibility of using computer vision techniques for human behavior monitoring through facial expression analysis (Shan, Gong et al. 2009, Shabbar Ameen 2014). Soukupová has developed a real-time eye blink detection algorithms using facial landmarks to detect human operators' vigilance (e.g. driver drowsiness)(Janssen, Rothkrantz et al. 2010). Reddy has developed a real-time driver drowsiness detection system by using facial landmarks of the drivers (Reddy, Kim et al. 2017). These studies show the potential of using facial expression analysis for detecting anomalous behaviors of ATCOs during air traffic control. One of the current study and focus is to use Bayesian Network (BN) modeling approach to quantify the relationship between anomalous behavior, human errors, and accidents by analyzing the accident reports from ASRS. Then examine how human behavior monitoring through facial expression analysis could help detect anomalous ATCOs' behaviors and use as real-time input to the BN for predicting human errors and accidents.

The work consists of two parts (see Figure 5): 1) develop a Bayesian Network (BN) to represent the quantitative relationship between anomalous behaviors of ATCOs, human errors, and accidents through a review of accident reports retrieved from ASRS. The developed BN provides risk knowledge about how anomalous behaviors of ATCOs cause human errors and lead to accidents according to the histories of ATC-related accidents; 2) develop a sensor-based human behavior monitoring algorithm to identify anomalous behaviors of air traffic controllers automatically. The developed algorithm first uses facial landmark detection to extract the Eye Aspect Ratio (EAR) as an observable feature. Then the algorithm uses the extracted EAR as input to the Hidden Markov Model (HMM) to detect anomalous human behaviors. The proposed approach uses the detected anomalous behaviors of ATCOs as inputs to the developed BN based on accident reports and provides probabilities of human errors and ATC-related accidents in real-time.

3.4. Uncertainty management and risk assessment

PHM for NAS needs to carefully include the effect of uncertainties for the safety assurance (Figure 1). Uncertainty management includes: uncertainty quantification, uncertainty propagation through models, uncertainty reduction technique in prognostics, and decision making under uncertainties. In large complex networks such as NAS, heterogeneous sources of uncertainty are involved in the process of risk assessment. These uncertainty sources in general can be classified into two categories: aleatory uncertainty and epistemic uncertainty (Mahadevan and Haldar 2000). Aleatory uncertainty sources are irreducible sources of variation such as measurement noise and physical variability in system characteristics (such as ground operations and pilot-to-pilot variations). Epistemic uncertainty sources are theoretically reducible that arise out of lack of perfect information such as environmental conditions and vehicle state. Rigorous uncertainty modeling frameworks for the risk assessment of NAS networks must be capable of accurately capturing the important statistical properties of the uncertainty sources (e.g. dependence over time and space between different uncertainty sources) and assess their contributions to the system performance. To enable this level of rigor, the system includes both probabilistic and non-probabilistic approaches to model the uncertainty sources. Probabilistic approaches are being used to quantify appropriate sources of uncertainty as random variables, stochastic processes, and time-dependent random field, modeled using probability distributions and correlations that describe interdependencies. Non-probabilistic approaches such as interval analysis, evidence theory, and fuzzy numbers are being used to create initial models for epistemic sources of uncertainty or where too little data is available to confidently fit the parameters of a probability distribution, and then equivalent probabilistic distributions are determined using the maximum entropy principle. In addition, rare events, which are usually the root causes of failures of the NAS systems, are often caused by simultaneous occurrences which are not only dependent but tail dependent (Bedford and Cooke 2002). Tail dependence measures the co-movement in the lower and upper tails of the joint probability function of uncertainty variables, which is important for the risk assessment of NAS.

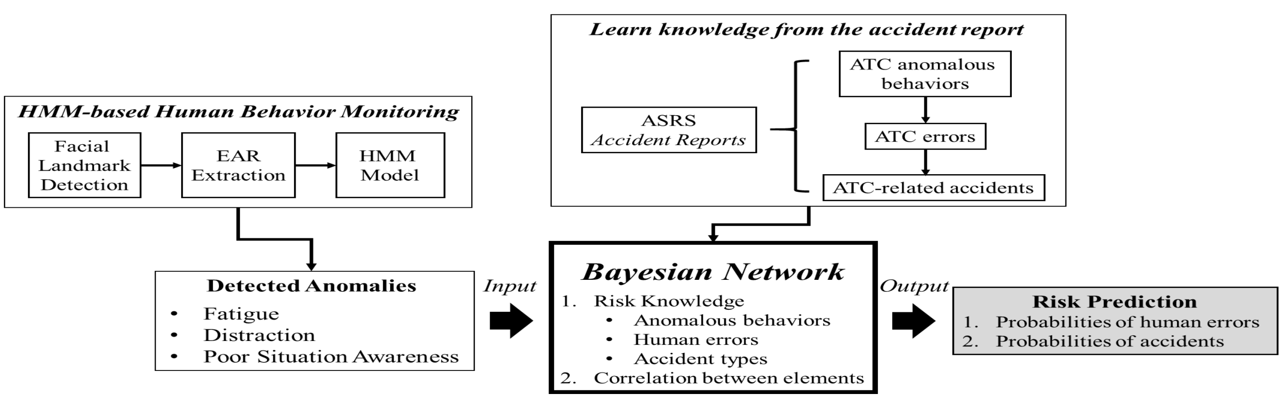
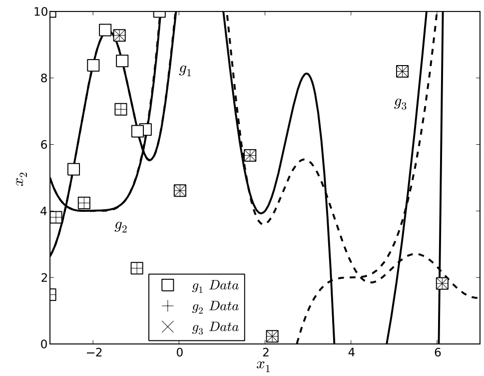


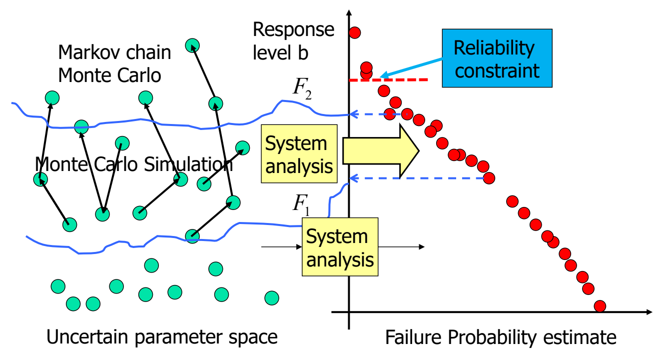
Figure 5. Flow chart for risk analysis integrating human monitoring

Because the NAS has an extremely large number of variables, it is necessary to evaluate the importance of each variable and thus reduce the number of variables to achieve the purpose of real-time risk assessment. Here, a fast global sensitivity analysis (GSA) method is being developed to determine the importance of variables in the NAS network. Current GSA methods for dimension reduction estimate the contribution of input variables to output variance (Wagner 1995) based on the variance decomposition theorem, and have two major limitations: (1) they only consider aleatory uncertainty in the inputs, and (2) in the presence of high-dimensional dependent variables, they are computationally expensive. The GSA method (Li and Mahadevan 2016a) is being leveraged to study complex NAS networks in the presence of correlated inputs and outputs, and extend it to fast GSA with both aleatory and epistemic uncertainty sources (Sankararaman and Mahadevan 2013) (due to noise, insufficient knowledge, data uncertainty, etc). Uncertainty sources with low contributions to output variability can be eliminated to enable real-time risk assessment.

After eliminating some of the input variables with low global sensitivity in the NAS network, the dimension of the remaining variables may still be high. In this situation, reduced-order modeling of the NAS networks from two main directions are being pursued, namely Sparse Principal Component Analysis (SPCA) (Zou, Hastie et al. 2006) and Active Subspace Modeling (Russi 2010, Constantine, Dow et al. 2014). SPCA is used to map the high-dimensional response variables of the NAS networks into low-dimensional latent variables. The main principle of SPCA is similar to the Principal Component Analysis (PCA), which uses orthogonal transformation to convert high-dimensional correlated variables into low-dimensional uncorrelated variables. Active subspace modeling is investigated to further reduce the input dimension. The directions of the remaining input variables with the largest variability is being identified first by exploring the gradient of the important principal components obtained from SPCA with respect to the remaining input variables. The BEN modeling of the NAS network is then implemented in the identified subspace (i.e., active subspaces). Next, surrogate models are constructed for the resulting input and response variables to build the BEN. The efficient global reliability analysis (EGRA) method (Bichon, Eldred et al. 2008) is one such method that constructs highly efficient Kriging models specifically for the purpose of risk assessment. EGRA has been shown to be especially effective when applied to system reliability problems that are necessary for assessing the NAS. An illustration of the EGRA method is shown in Figure 6(a).



a)



b)

Figure 6. Illustration of a) EGRA and b) inverse subset sampling algorithms

The above discussion is for forward risk assessment and reliability analysis where all the input variables are determined. Another critical element in the discussed research is the inverse reliability analysis, i.e., determine the remaining useful life (prognostics) or model parameter value (design) given the required reliability level of the system.

The inverse reliability problem is essentially an optimization problem with reliability constraints. Reliability-based design optimization (RBDO) has been widely investigated in the past. In general, the methods can be divided into gradient-based RBDO problem with analytical formulation and sampling-based simulation algorithms. For the former one, several inverse reliability algorithms have been developed by different researchers (Li and Foschi 1988, Ramu, Qu et al. 2006) (Kirjner-Neto, Polak et al. 1998). One of the most widely used analytical method is the inverse first-order reliability method (FORM) (Xiang and Liu 2011). The key idea is to iteratively use the Taylor linear approximation of the defined limit state function until the convergence of the performance function and the constraint function. The benefit is the very efficient calculation for medium-size problems, which is critical for the first-order determination of the complex NAS system once the reduced-order model is available. Real-time risk assessment can be done with the help of inverse FORM.

If more detailed risk assessment is required with large systems, the inverse FORM-type of analytical inversion technique is not appropriate. First, numerical difficulties may occur when calculating the gradient of response function in the searching process, especially for an implicit response function. Second, the complex NAS network may yield very complicated limit state function shape and multiple failure envelopes. In view of this, efficient simulation algorithm with novel sampling method, such as Subset Simulation (Au and Beck 2001), is explored. The Subset Simulation is an efficient Monte Carlo technique originally developed for structural reliability problems. In this method, a small probability problem is decomposed into a series of large conditional probabilities. Then, the method takes advantage of the Markov Chain Monte Carlo (MCMC) (Li, Xiang et al. 2012) to estimate the small probability. A schematic illustration of the discussed inverse subset simulation is shown in Figure 6(b).

3.5. Information fusion and prognostics

One of the key concept for a complex system prognosis is rigorous information fusion (Figure 1). The key idea is to integrate all available information (archived or real-time) to assist the final objective of PHM. Above discussion presents many different types of information available in NAS and a novel Bayesian Entropy Network (BEN) is used for this purpose. BEN is a generalized Bayesian Network (BN) where Entropy is used to enrich the inference if additional information constraint is available. Bayesian Network (BN) has been widely used for causal studies where the topology structure represents the causal relationships. Existing BN methods for causal inference only take the information from point observation/experimental data. Many other sources/types of information cannot be directly used by the BN. For example, these types of information include non-probabilistic range information, linguistic information/opinions from human, physical constraints, and encoded probabilistic point data (e.g., only moment information is available due to data reduction). Rigorous and systematic inclusion of multiple sources information is critical for a complex system-of-systems such as the NAS. A new definition of Maximum Relative Entropy is used for inference and prognostics

$$S[P_{new}, P_{old}] = -\int P_{new}(x,\theta)\log\frac{P_{new}(x,\theta)}{P_{old}(x,\theta)}dxd\theta \qquad (1)$$

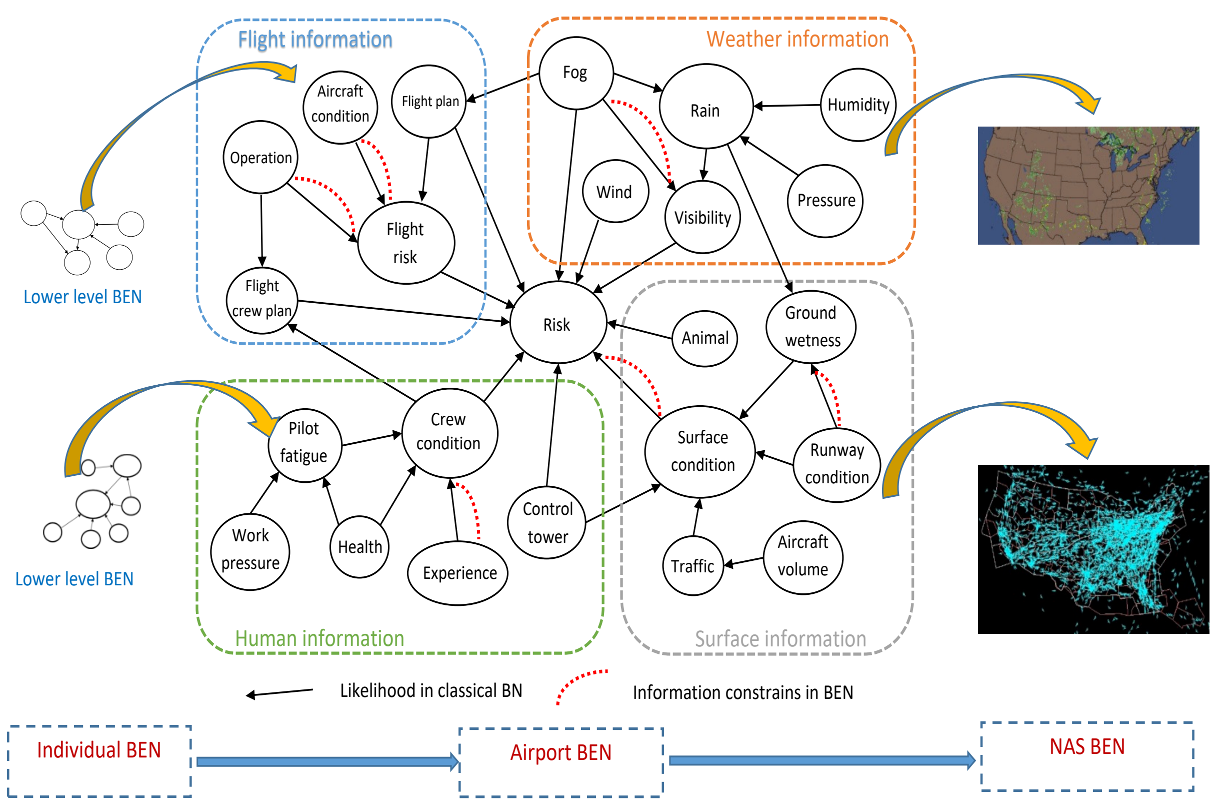


Figure 7. Schematic illustration of the multisource hierarchical information fusion of NAS using BEN

where x is the observed data and θ is the model parameter. P_{old} is the joint prior distribution and P_{new} is the joint posterior distribution. $S[P_{new}, P_{old}]$ is the relative entropy. Additional information can be coded as constraint $f(\theta)$

$$\int P_{new}(x,\theta)f(\theta)dxd\theta = \langle f(\theta) \rangle = F \qquad (2)$$

By maximizing the relative entropy (Guan, Giffin et al. 2012), the posterior of model parameters given the new information (i.e., point observation data x and constraints $f(\theta)$) can be obtained as

$$P_{new}(\theta) = \frac{P_{old}(\theta)P_{old}(x \mid \theta)e^{\beta f(\theta)}}{\int P_{old}(\theta)P_{old}(x \mid \theta)e^{\beta f(\theta)}d\theta} \qquad (3)$$

The Lagrange multiplier β is determined by the optimization. Eq. (3) shows that the updating is identical to the Bayesian updating if no additional constraints are given, i.e., $f(\theta) = 0$. This formulation is termed as Bayesian Entropy (BE) updating. The above discussion can be considered as a single "node" problem and can be extended to its network format. Thus, Bayesian Entropy Network (BEN) can be developed and it has the same topology structure and algorithmic properties as the classic Bayesian Network (BN) (Wang & Liu, 2018). The developed BEN are used for the causal multiscale inference, information fusion, and prognostics as shown below.

Information fusion in the discussed study integrates all achievements from previous components. Some of the characteristics of the NAS networks are that they are hierarchical (e.g., NAS system – airport portal node – vehicle level monitoring) and dynamic (time-dependent processes) in nature. An example of the hierarchical multisource dynamic BEN for NAS systems is shown in Figure 7.

Here, the BEN concept and the Dynamic Hierarchical Bayesian Networks (DHBN) (Nannapaneni) are being combined for the integration of knowledge and aggregation of uncertainty sources across levels and time of the NAS networks. A BEN in general, can be constructed in three ways – (1) using physics-based models, (2) using data-driven models, and (3) a hybrid approach, combining physics-based and data-driven methods. Currently available techniques, such as greedy hill-climbing, minimal description length, Bayesian-Dirichlet equivalence, and Mutual Information Test (MIT) is under investigation to facilitate automatic DHBN learning of NAS networks.

Next, the information fusion from both domain-knowledge and data is performed. Domain knowledge and expert's opinions have their preferences of the network structure and topology (dimensions). Automatic and efficient determination of most proper model and model combinations are very valuable for the prognostics. A reversible jump Markov Chain Monte Carlo (r-MCMC) simulation (Guan, Jha et al. 2010, Guan, Jha et al. 2011) are being developed and used to automatically learn the most plausible topology structure from different types of information. The most plausible causal inference results can be automatically identified using the r-MCMC samples. Finally, the developed method is extended for dynamic complex system with possible topology structure changes with help of DHBN algorithm. Developing an efficient algorithm for moderate-to-large size networks with the time-evolving nodes is the key focus.

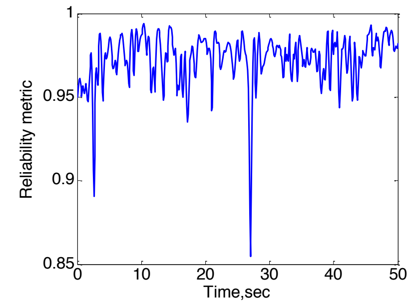
It should be kept in mind that the above discussion is on the fundamental algorithm developed for information fusion. Information fusion in a complex system such as NAS involves frequent communication and flow of huge amount of data. These data are hierarchical and dynamic at both temporal and spatial scales. The key objective of "real-time" information fusion thus requires very rigorous management of information flow to avoid overflow and over-reduction.
The discussed approach for real-time information fusion is to map the functionalities of information fusion in BEN to physical devices of the NAS network in resource-constrained environments. In the information fusion network, data objects include original (or raw) data such as sensor measures or expert opinions, intermediate data after local processing, and final risk assessments. To aggregate information from multiple sources, a protocol for distributed information stream management is required to decide where to cache, where to process, and how much to transmit based on the state of NAS and the risk levels. To tackle the challenge of prognostics-based information stream management in the NAS network, an optimization-based approach for the design of distributed information stream management protocols is being explored. An NSA network can be represented as a graph where the nodes correspond to physical devices such as a sensor or an airplane, possibly with limited power and energy (e.g., a sensor node), and the edges represent communication links with limited and time-varying bandwidth. In recent work (Wang and Ying) a throughput optimal information stream management protocol has been developed that includes load-balancing, information transmissions and data-processing scheduling.

3.6. Verification, validation, and safety assurance

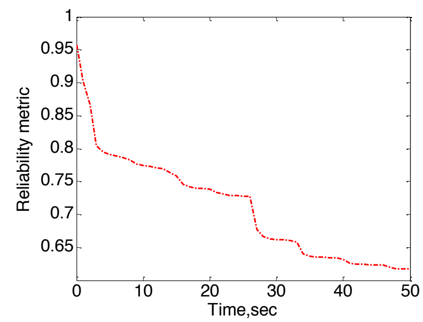
Verification and Validation (V&V) methods for the cyber-physical-human NAS systems is required for future certification and decision-making (Figure 1.). NAS is a highly complex heterogeneous system, featuring interactions between hardware, software, and human operators and users. The discussed methodology systematically organizes the available models and information in order to develop system-wide confidence in the NAS simulation models. Since NAS systems are hierarchical and dynamic in nature, new verification and validation metrics is developed from the dynamic risk assessment perspective. Currently available verification and validation metrics mainly focus on problems of static response prediction. These metrics is extended to dynamic response of complex networks, based on random process representation and principal component analysis over time. The new V&V metrics are being developed from two directions, namely feature-based validation metrics and reliability metric-based validation metrics. In the feature-based validation metrics direction, wavelet analysis (Jiang and Mahadevan 2008), principal component analysis, and time-series modeling are leveraged to the development of V&V metrics for large complex systems. In the reliability metric-based validation metrics (Mahadevan and Rebba 2005, Rebba, Mahadevan et al. 2006), V&V metrics are being investigated from the perspective of time-dependent reliability. Three different metrics appear feasible – instantaneous reliability, first-passage reliability, and accumulated reliability – each offering a different measure of model performance. Figure 8 gives an illustrative example of the V&V metrics for time-dependent complex systems. The V&V metrics developed in the feature-based methods and reliability metric-based methods have their own advantages and disadvantages. The information obtained from these different V&V analyses are being fused in a Bayesian network to develop an overall performance assessment of the NAS models. The developed dynamic V&V metrics effectively capture the quality change of the NAS models over time and thus provide a real-time model assessment.

Model assumptions and approximations are inevitable during NAS simulation and risk assessment. These assumptions and approximations constitute model uncertainty. Along with model uncertainty, there is also data uncertainty (due to sparse, imprecise, erroneous, missing or qualitative data) (Sankararaman, Ling et al. 2011), causing uncertainty regarding the inputs to the NAS model. The model and data uncertainties cause uncertainty in the results of V&V and system risk assessment (Sankararaman and Mahadevan 2011). Rigorous verification and validation (V&V) need to be performed at both component and system levels in order to establish adequate confidence in the analysis results. The developed new V&V metrics are being extended to incorporate heterogeneous sources of data uncertainty into the V&V metrics using Bayesian networks. In addition, effective UQ methods, which quantify the uncertainty of V&V results due to model and data uncertainty, need to be included in V&V process.

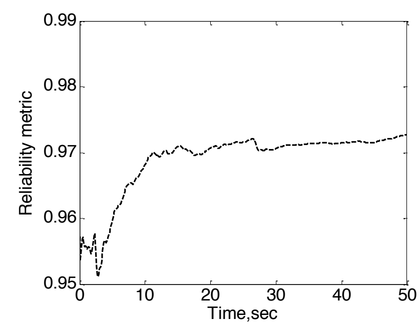
An important element in information sourcing is sensitivity analysis, which helps to identify the dominant contributors to prognosis and validation uncertainty, and system safety. A particular benefit of the sensitivity analysis is to optimally allocate resources for uncertainty reduction activities (such as data collection, testing, model refinement, etc.) (Sankararaman, McLemore et al. 2013). In the discussed effort, the solution of this inverse problem is accomplished through multi-objective optimization methodologies suitable for complex cyber-physical-human systems. Our previous research on the validation of safety analysis using BNs and resource allocation for model validation (Li and Mahadevan 2016b) is implemented to develop a new resource allocation strategy for model validation of NAS systems. The GSA method is used to provide guidance on where and when should the validation be conducted through uncertainty contribution analysis of components and subsystems towards the uncertainty in the overall system.



(a) Instantaneous



(b) First passage



(c) Accumulated

Figure 8. Illustration of the model reliability metric for dynamic systems

4. CONCLUSIONS

This paper addressed the safety needs and their technology solutions for future NAS. Because the NAS is a fully coupled cyber-physical-human system, a number of technologies and supporting techniques need to be interlinked to provide the desired safety at an acceptable performance level. Backbone to the methodology is an information fusion and uncertainty management framework. The underlying premise to ensuring safety is the need to assess and predict the evolution of the airspace's safety state. Towards that end the following elements are pooled and conjoined: modeling of the airspace using both data-driven and physics-based approaches; quantifying and managing uncertainty; advancing prognostics and information fusion algorithms; and understanding and modeling human computer interface. A comprehensive simulation environment is being built that will assess performance and allow verification and validation. The techniques presented here are part of the NASA University Leadership Initiative (ULI) collaborative project that specifically addresses NASA Aeronautics strategic thrust 5: Real-Time System-Wide Safety Assurance.

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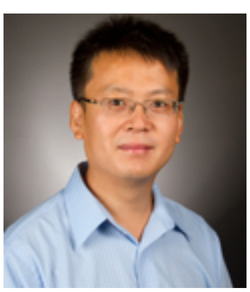
BIOGRAPHIES



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