OBJECT-ORIENTED BAYESIAN NETWORKS (OOBN) FOR AVIATION ACCIDENT MODELING AND TECHNOLOGY PORTFOLIO IMPACT ASSESSMENT

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Abstract

The concern for reducing aviation safety risk is rising as the National Airspace System in the United States transforms to the Next Generation Air Transportation System (NextGen). The NASA Aviation Safety Program is committed to developing an effective aviation safety technology portfolio to meet the challenges of this transformation and to mitigate relevant safety risks. The paper focuses on the reasoning of selecting Object-Oriented Bayesian Networks (OOBN) as the technique and commercial software for the accident modeling and portfolio assessment. To illustrate the benefits of OOBN in a large and complex aviation accident model, the in-flight Loss-of-Control Accident Framework (LOCAF) constructed as an influence diagram is presented. An OOBN approach not only simplifies construction and maintenance of complex causal networks for the modelers, but also offers a well-organized hierarchical network that is easier for decision makers to exploit the model examining the effectiveness of risk mitigation strategies through technology insertions.

Introduction

The air transport system is fast growing; the public benefits from this continued growth depend on the safe, efficient and effective operations of air vehicles. With significant demand in aircraft operations, the Next Generation Air Transportation System (NextGen) concept of operations are developed to transform the existing air travel system, achieving an operation of exceptional levels of safety, flexibility, efficiency, and robustness in a more complex and demanding environment. With the anticipated increase of travel and new operations in NextGen, aviation safety and risk which have always been issues of a great importance due to the inherent complexity and severe accident consequences now become all more pressing.

The overall goal of the NASA Aviation Safety Program (AvSP) is to "conduct cutting-edge research that will produce innovative concepts, tools, and technologies to improve the intrinsic safety attributes of current and future aircraft," (Shin, 2011). The AvSP uses the results of systems analyses, assessments and studies for programmatic decision-making, safety research portfolio prioritization and communication. A qualitative system analysis of the NASA AvSP was conducted to identify historic and future safety issues and to evaluate the potential impact of the AvSP technology portfolio on these issues (Jones et al., 2010). This qualitative assessment provided a better understanding of the potential impact of the AvSP technology portfolio on aviation safety, but was lacking any quantitative analysis of the impact of these aviation technology products on safety risk mitigation. To this end, a quantitative analysis approach was needed that: (1) was flexible and robust to model complex aviation accidents and (2) provided the capability to assess the portfolio impact on the reduction of aviation system risk while the current air transportation system is transformed to NextGen operations.

In this paper, a brief review is given to some commonly used aviation risk and safety methods/models as a path to select an appropriate probabilistic methodology and software package for the set purposes. The object-oriented Bayesian Belief Network (OOBN) suggested in this paper lends itself to large and complex aviation accident modeling and technology portfolio assessment. In addition to having all the features (inference and updates) as a traditional Bayesian network, the object-oriented concept allows modular, less-cluttered designs of a complex causal model in a dynamic environment. To illustrate the benefits of applying OOBN, the paper includes a loss-of-control (LOC) accident model constructed using Hugin Expert (Hugin, 2012) software*. The technology portfolio evaluation is conducted through the incorporation of safety products as decision nodes in the model. The projected impact of the AvSP products on the accident risk is assessed by comparing the predicted likelihood values of LOC with and without the products.

Overview of Aviation Risk and Safety Methods/Models

Researchers at the National Aerospace Laboratory of the Netherlands (NLR) identified more than 720 safety methods (Everdij et al., 2010), and over 100 of these have been applied in aviation domains. The purpose of these qualitative and quantitative risk and safety methods/models is to discover and describe primary causes of aircraft accidents in order to prevent future accidents. In addition, the causal methods/models can evaluate the benefits of different risk interventions from safety technologies. An exhaustive research of aviation safety methods/models (GAIN Working Group B, 2003; Netjasov and Janic, 2008) is beyond the scope of this study. However, the key concepts of some popular methods/models are briefly reviewed and compared in the context of the current objectives of aviation accident modeling and portfolio impact assessment.

Methods. The Fault Tree (FT) method (Vesely et al., 2002) is a top-down approach, starting with a top event that is a failure or a hazard with serious consequences, followed by several paths representing different combinations of events or causes described with logical operators (AND, OR, etc.). The logic in FT is binary. The probability of occurrence and non-occurrence of each event is assigned, the probability of the top event is then computed. The FT method is a causal analysis and is favored when combinations of failures are expected, and is mostly used for quantitative risk and reliability studies, such as the failure analysis of systems.

The Event Tree (ET) method (Stamatelatos and Dezfuli, 2011) is a forward method beginning with an initiating event or condition. ET is used to model chronological sequence of events and consequences (or outcomes) of the initiating event through a series of potential paths. Each event has a finite set of states, commonly two states, with assigned probabilities, the probability of various possible outcomes can then be computed. An ET is particularly useful in developing multiple safeguards to reduce the unwanted consequences of the initiating event. ET is a consequence analysis and depicts the sequence dependencies, which differs from FT. However, Event Trees are often used together with Fault Trees that analyze the causes of the hazardous event that initiates the accident sequence.

An Event Sequence Diagram (ESD) method (Stamatelatos and Dezfuli, 2011) is a scenario analysis used to describe a set of possible risk scenarios originating from an initiating event. The initiating event is typically an anomaly (event causing deviation from normal operation) or a system component failure. Along each scenario path, pivotal events are identified as either occurring or not occurring. Each scenario leads to a final end state, indicating the outcome of that scenario. The concept of an ESD is similar to an ET, both illustrate the progression of events over time. However, the scenarios are usually kept broad, the detailed causes or specificities of these events are not directly of interest at the scenario level. An ESD, like ET, is often combined with FTs that model the details of initiating and pivotal events in ESD.

A Bayesian Belief Network (BBN) is a directed acyclic graph that provides a network-based framework to represent causal models for reasoning under uncertainty (Korb and Nicholson, 2004). A BBN consists of a set of nodes representing causal variables, and a set of the directed arcs (or links) connecting the nodes showing the causal dependencies. Each variable has a finite set of mutually exclusive states. The causal relations between variables are expressed in terms of conditional probabilities. The probability computation is based on Bayes' theorem (Jensen and Nielsen, 2007). Unlike the FT and ET, the BBN is able to represent the multi-dependencies between causal factors that lead to the final consequence in complex systems. Additionally, BBNs has been used as a decision-support tool through the application of the Bayesian Decision Theory and the Influence Diagram (ID) with decision nodes and utility nodes in the networks.

Models. The Aviation System Risk Model (ASRM) (Luxhoj, 2004) is a decision support system designed to estimate the system risk and assess the impacts of new safety technologies insertions/ interventions using traditional BBNs and ID. The ASRM contains a collection of BBN models that model the interactions of aviation system risk factors focusing on the human-induced causal factors. The Bayesian probability and decision theory are used to quantify the accident likelihood and to evaluate impacts of multiple new safety technology insertions/interventions. Models in ASRM are accident-based case models in selective aviation accident categories.

The Causal Model for Air Transport Safety (CATS) models (Ale et al., 2009) the gate-to-gate causes of commercial air transport accidents and the safeguards in place to prevent hazards leading to accidents. The purpose of CATS is to quantify the risk of air transport estimating an accident probability per flight. The CATS models the underlying causes in the complex aviation system by constructing separate causal models for each considered accident category (loss of control, collision, etc.) in each flight phase. The CATS combines three modeling techniques in a single model: ESDs, FTs and traditional BBNs. The ESDs and the FTs are converted into BBNs and from that the integrated CATS BBN is built to compute the probability of an accident.

The Quantitative Risk Assessment System (QRAS) (NASA HQ/OSMA, 2002) is a comprehensive PC-based Probabilistic Risk Assessment (PRA) tool for conducting an integrated system safety, reliability and risk assessment of safety critical systems. QRAS technical approach is to divide a complex system's risk model into time-phases and to allow different failure modes being modeled in each operational phase along the mission time-line. QRAS employs ESDs, ETs and FTs, and can aggregate the probabilities of all initiating events to obtain the probability of failure at various levels - system, subsystem, component, and failure mode. QRAS includes a rich suite of quantification models to specify the probability distribution for the events, and the uncertainty distribution on the probability.

While Fault Tree and Event Tree methods are common techniques for analyzing large complex integrated systems, their linear causal or time order approach fails to adequately represent the uncertainty and multi-dependencies between causal factors in a complex system like an aviation accident. In contrast, Bayesian networks provide a framework that represents the logical multiple cause-effect relationships among factors (or variables) and captures the uncertainty in the dependencies between factors using conditional probabilities. In addition to a rigorous mathematical treatment for complex accident causal modeling, a BBN has the ability of being an Influence Diagram as a decision tool to evaluate the effect of new safety technologies on the model. Moreover, inference on a BBN can be conducted by entering the evidence when the knowledge of node states is obtained through other means, such as empirical evidence or experiential database. Although there are some unique features in ASRM, CATS, and QRAS, their underlying methodologies and software tools are not readily applied to achieving the objectives of having generalized accident models inclusive of human-environment- and systems-induced causal factors, and of assessing the technology portfolio impact on the aviation safety. In summary, the authors adopt the use of BBNs as the fundamental technique to model critical aviation safety issues and to assess AvSP technology portfolio on the safety risk reduction.

The Choice of a BBN Software

For the modeling exercise being considered, it needs a Bayesian causal modeling tool with a graphical front end for BBNs' construction and a computational engine for the Bayesian analysis. A variety of BBN software packages are available from both commercial vendors and the public-domain. No attempt was made to provide a list of the Bayesian causal modeling tools or to rank these packages, instead (Korb and Nicholson, 2004) and (Murphy, 2012) are offered for learning more of the BBN software packages. This section will focus on the desired features of a BBN tool for its intended use for the given task. It is authors' viewpoint that the following features are required or highly favored:

(1) Influence diagrams capability: BBNs can be extended with decision and utility nodes to form an influence diagram for decision making in the context of assessing technology portfolio impact and evaluating the aviation safety risk.
(2) Modular and hierarchical capability: BBNs for aviation accidents models will be large and complex. With modular designs, a complex system can be efficiently built by combining modules (or sub-models), which are constructed simultaneously by different modelers. The structured methods of modularity and hierarchy help control the complexity and the development of large-scale BBNs. If a BBN has some structure or better organization, the computational performance is likely enhanced.
(3) Computational efficiency/performance: For a large complex network with many nodes and dependencies, the probabilistic calculations can be tedious and very difficult. The software tool must implement efficient BBN analysis algorithms to solve complex problems.
(4) Maturity: The tool should have undergone rigorous development and testing processes, and have proven record of its successful applications in a wide range of modeling domains, including aviation areas.
(5) Application Program Interface (API): For the potential task growth, it is desirable that the software's API is available for different popular languages, such as C++, Java, Visual Basic, and can run on a broad platform, including Windows, Mac, and Linux operating systems. The API enables a modeler to include BBN operations in his application programs, and allows the interaction between BBNs and applications, such as Microsoft Excel or Access.
(6) Software maintenance and technical support: The tool should be well documented and maintained by the software developers to ensure the software's integrity and quality. A responsive and experienced technical support team is important to the end users.
(7) Cost for multiple licenses at different user locations: It is envisioned that aviation accident modeling tasks are multiple and may be conducted by NASA personnel at different geographical locations. The available license format and its cost-effectiveness are also in consideration.

Based on the selection criteria for the intended use, the Hugin software has many advantages over competing tools, including Netica and BNet. The attractive merits of Hugin include the ability to represent and efficiently solve complex decision-making problems with influence diagrams, and to allow complex domains to be described in terms of inter-related modules using object-oriented BBNs (OOBNs). The following section will introduce the key concepts of an OOBN, and demonstrate its application in a loss-of-control accident modeling.

Application of OOBNs for Accident Modeling and Portfolio Assessment

An OOBN (Koller and Pfeffer, 1997) is an extension to BBNs with a set of basic object (i.e., a standard variable node) and complex object (i.e., an instance node). An instance node is an instantiation of a network class, or an abstraction of a network fragment into a single unit. An instance node connects to other nodes via interface nodes– input and output nodes. Represented as an instance node, the encapsulated network (or sub-model) becomes modular. Modularity facilitates the reuse of nodes and network fragments of an object in the same network or a different network. Another trademark of the object-oriented approach is the ability to define classes that inherit the properties of other classes plus additional attributes of its own. Furthermore, in contrast to a traditional BBN represents only the probabilistic relationship among a set of variables at some point in time, an OOBN is able to model temporal relationships among variables for dynamic structures. In summary, the salient features of OOBN modeling include abstraction, encapsulation, hierarchy, inheritance, interface, and modularity.

Exhibit 1 is a top-level depiction of the generalized loss-of-control accident framework (LOCAF) constructed by the Hugin software. LOCAF is a large and complex causal model comprising causal and contributing factors to the loss-of-control accidents from three different domains, namely, the aircraft system, human (both flight crew and ground personnel), and external atmospheric environment. The details of the development, quantification, and analysis of LOCAF are given in (Ancel and Shih, 2012) and (Luxhoj et al., 2012). The discussion here is centered on illustrating the application of OOBN concepts and BBN decision-making in LOCAF. In addition to the oval-shaped chance nodes for standard random variables, the top-level topology of LOCAF includes three instance nodes displayed as rounded rectangles representing encapsulated sub-networks. Every instance node has a descriptive node name representing the internal sub-network that is hidden from the top-level view. Meanwhile, every instance node contains interface nodes that are visible and link to other nodes in the top-level view or/and other sub-networks. In this example, three sub-networks are regarded as three sub-models in BBNs, respectively describing the causal contributions to the LOC due to the flight crew conditions before entering the cockpit, environmental conditions, and aircraft system component failures.

Exhibit 2 displays the environmental sub-network, while Exhibit 3 and **Error! Reference source not found.** show two separate sub-models in the System Component Failure (SCF) domains in LOCAF, accounting for the causal contributions from the aircraft systems and maintenance. There are two output nodes drawn with thick borders in the environmental sub-model, which are made visible in the green-colored instance node of Exhibit 1, the top-level model, and of Exhibit 3, one of SCF sub-models. It should be noted that only one output node (and a different one) is used to connect to other node(s), respectively, in Exhibit 1 and Exhibit 3. This demonstrates the modularity and reusability of the environmental sub-model, as well as the network flexibility that simplifies the model construction. The concepts of hierarchy and multi-level of abstraction are manifested in system component failure instance node (in Exhibit 1) to which two deeper levels of sub-networks are attached. The successively embeded sub-layer networks are shown in **Error! Reference source not found.**, and then Exhibit 3 and **Error! Reference source not found.**. Applying this OOBN approach, LOCAF top-level view reveals all the essential components of this model, and spares the overall complexity of the network for better communication and explanations. The complex sub-models are hidden in the instance nodes. Models reusability and techniques of encapsulation lessen the amount of work involved in building such a large network.

Exhibit 1. Top-level Depiction of the Generalized Loss-of-control Accident Framework (LOCAF).

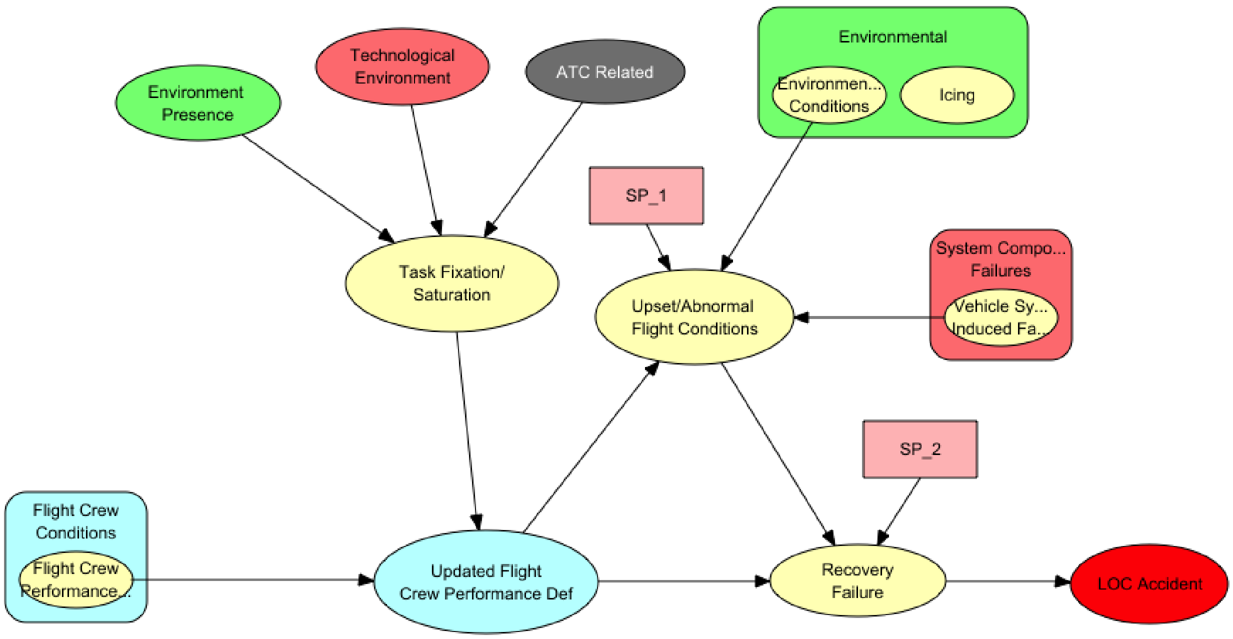


Exhibit 2. Environmental Sub-model for LOCAF.

Exhibit 3. System Component Failure Sub-model for Aircraft System.

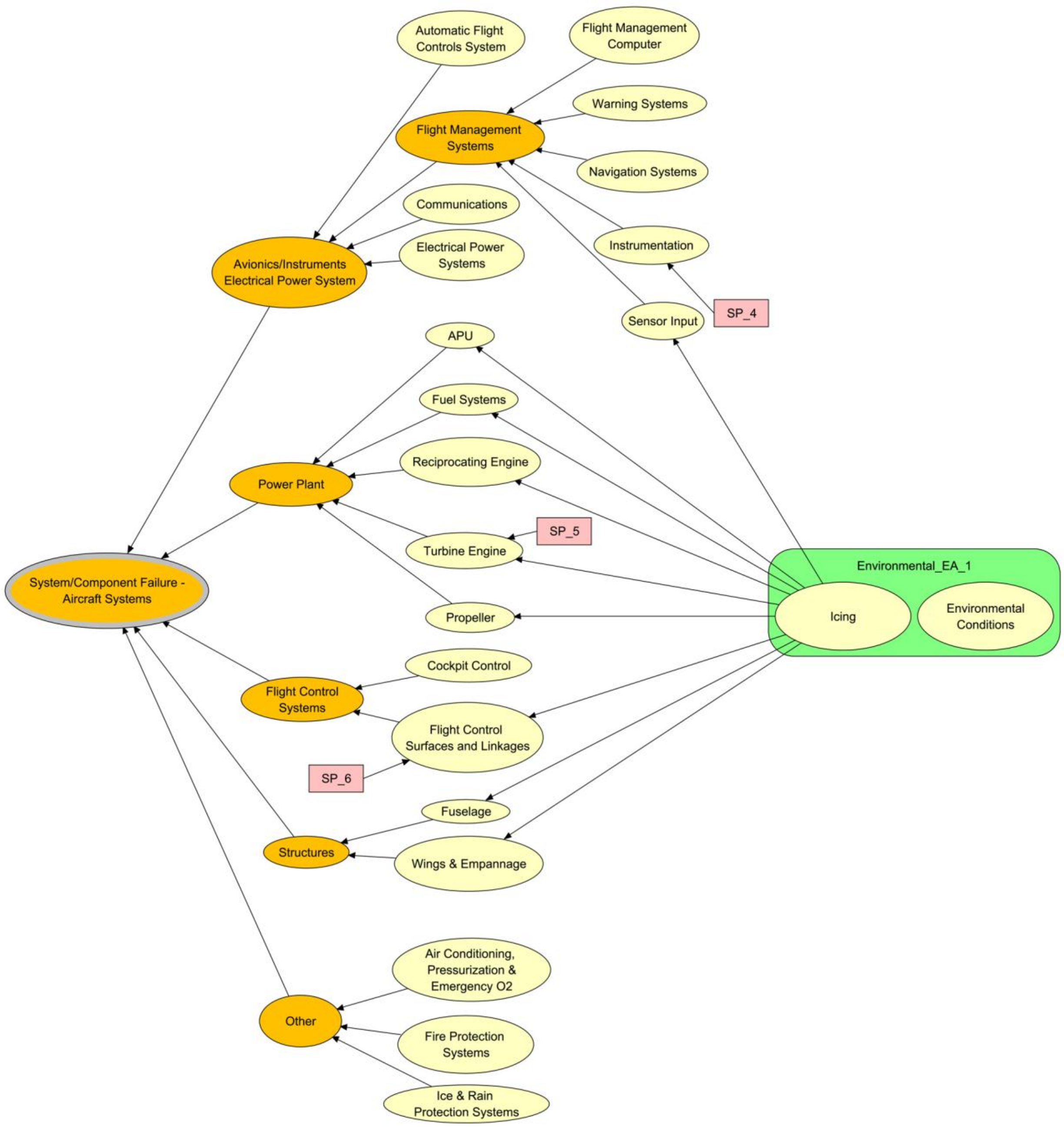


Exhibit 4. System Component Failure Sub-model for Maintenance.

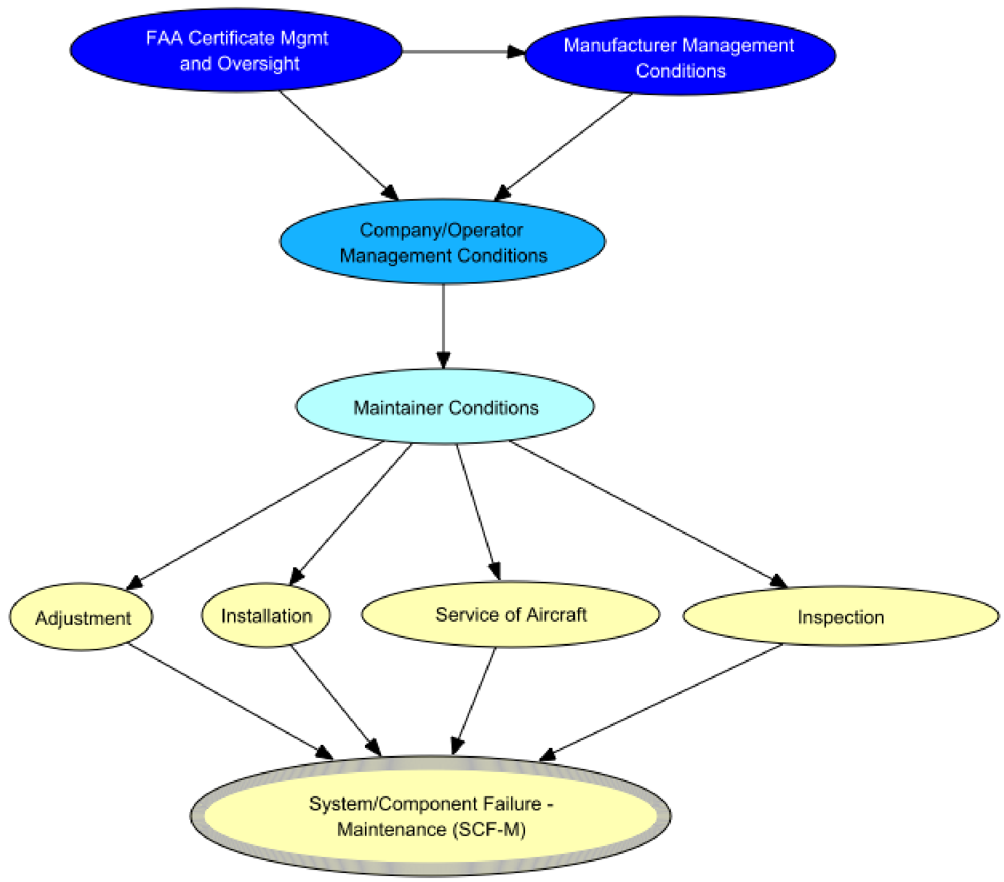
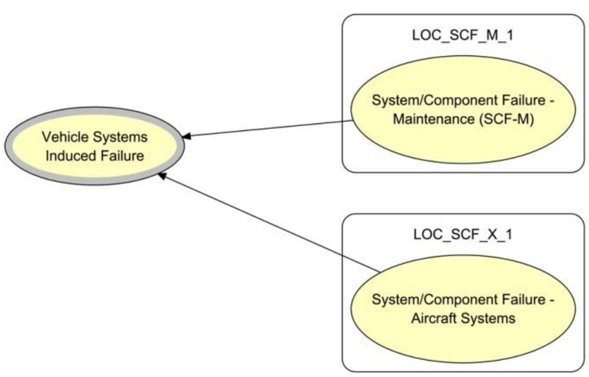


Exhibit 5. Multi-level Abstraction of the System Component Failure Network.



There are many new safety products in the technology portfolio, the intervention/mitigation of these safety products is introduced into LOCAF as rectangular-shaped decision nodes. With the products in decision nodes, the model is now referred to as an Influence Diagram. A decision node is connected to those causal variable nodes whose probability distributions are directly affected by the decision policy of either implemented or not-implemented. As shown in Exhibit 1- Exhibit 3, the decision nodes appear in both top-level network and sub-networks in LOCAF. The comparisons of computed likelihood values of the occurrence of LOC (LOC Accident node in Exhibit 1) with and without safety products give the projected impact of safety technologies on the LOC risk. In addition, the sensitivity analysis can be performed on LOCAF to rank the most influential causal nodes to the LOC node. This information helps strategize the safety technology investment and establish an effective technology portfolio.

Conclusions

NASA AvSP takes on the challenge of developing a technology portfolio to meet the anticipated increase in aviation safety issues, particularly, arising from the transformation of current airspace transport system to the NextGen operation. This paper presented a brief review on aviation risk and safety methods/models, and the criteria for selecting an appropriate methodology and software tool for the aviation accident modeling and portfolio impact assessment. The Object-Oriented Bayesian Belief Network (OOBN) approach was very suitable when modeling complex aviation accidents (or safety issues) that are influenced by interactions of different domains, including human operators, atmospheric environment, and aircraft systems and components. Techniques of encapsulation and model reusability add to the simplification, flexibility and portability in model development. For an illustrative purpose, a loss-of-control accident model was introduced to show the benefits of OOBN and the evaluation of safety technology portfolio.

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