A PROBABILISTIC METHODOLOGY TO IDENTIFY TOP CAUSAL FACTORS FOR HIGH COMPLEXITY EVENTS FROM DATA

by

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DEDICATION

I dedicate this dissertation work to my loving and encouraging wife, Bina, and to my adorable kids, Nathan and Caleb. I owe my personal and professional success to their unreserved love and support.

I also dedicate this dissertation to my father, Bati Wahelo, who instilled in me the value of education since I was a little boy.

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Finally, I am so grateful to my entire family for putting up with years of my late nights.

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LIST OF ABBREVIATIONS

Accident/Incident Data System........ AIDS
Air Traffic Control Assigned Airspace........ATCAA
Air Navigation Service Provider........ ANSP
Air Traffic Control........ATC
Air Traffic Organization of FAA........ ATO
Application Programming Interface .... API
Artificial Intelligence........ AI
Aviation Safety Action Program........ ASAP
Aviation Safety Reporting System........ASRS
Aviation Traffic Safety Action Program........ATSAP
Bayesian Belief Network .... BBN
Brier Score, a probabilistic classification accuracy metric........BS
Causal Model for Air Transport Safety .... CATS
Conditional Probability Distribution........CPD
Controller Alerting Aid for Tracked Aircraft ....LA/MSAW
Directed Acyclic Graph ....DAG
Event Sequence Diagram........ESD
Expected Utility .... EU
Extensible Markup Language ....XML
Fault Tree........FT
Federal Aviation Administration of USA........FAA
Human Factors Analysis and Classification System ....HFACS
ICAOs Accident/Incident Data Reporting System .... ADREP
Instrument Flight Rules........ IFR
Instrument Meteorological Conditions ....IMC
International Civil Aviation Organization ....ICAO
Likelihood Scoring........LS
Line Operations Safety Audit ....LOSA
Low Probability-High Consequence........ LP/HC
Maximum Likelihood Estimation........MLE
Minimum Description Language ....MDL
Modeling Aviation Risk........ ASRM
National Aeronautics and Space Administration of USA........NASA
National Airspace System of USA ....NAS
National Transportation Safety Board of USA........ NTSB
Near-Mid Air Collision........NMAC

No Radio .... NORDO
Operational Error & Deviation .... OED
Probabilistic Graphical Model .... PGM
Safety Management System .... SMS
Safety Risk Management .... SRM
Search and Testing for Understandable Consistent Contrasts .... STUCCO
Service Difficulty Reports .... SDR
Subject Matter Expert .... SME
Temporary Flight Restriction .... TFR
Traffic Collision Avoidance System – Resolution Advisory .... TCAS RA
Tree-Augmented Naïve .... TAN
Visual Flight Rules .... VFR
Waikato Environment for Knowledge Analysis .... WEKA

ABSTRACT

A PROBABILISTIC METHODOLOGY TO IDENTIFY TOP CAUSAL FACTORS FOR HIGH COMPLEXITY EVENTS FROM DATA

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George Mason University, 2014

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Complex systems are composed of subsystems and usually involve a large number of observable and unobservable variables. They can be modeled by determining the relationship between the observable factors (features) or their abstractions and the target (class) variables in the domain. The relationship is defined by a hierarchy of factors, categories, sub-categories, and the target variables. The factors, categories, and sub-categories are groupings of all the variables, and are represented as artifacts in the model which can be generated from real-world data. In safety risk modeling based on incident/accident data, the target variables are the various events and the features represent the causal factors.

The National Airspace System (NAS) is an example of a safety-critical domain. The NAS is characterized by several datasets. One of the datasets, the Air Traffic Safety Action Program (ATSAP), is designed to capture Air Traffic Control (ATC) related

safety data about the NAS. The ATSAP defines ATC domain with more than 300 observable factors and 21 undesired events along with other miscellaneous variables. There are more than 70,000 ATSAP incident reports between 2008 and 2013. Developing a useful model of safety for the NAS using the ATSAP dataset is prohibitively complex due to the large number of observable factors, the complex relationships between observed variables and events, and the probabilistic nature of the events.

Probabilistic Graphical Models (PGMs) provide one approach to develop practical models that can overcome these difficulties and be used for safety analysis and decision-making. This dissertation describes an approach using a class of PGM called Bayesian Networks to develop a safety model of the NAS using ATSAP data. The modeling technique includes approaches to abstract hierarchical relationships from observable variables and events in the domain data by: (1) creating categorical variables from data dictionary to abstract sub-categories and lowest level observable variables in the hierarchy, and by (2) calculating the probability distribution of the categories from their low level categories or observable variables.

The models can be used to identify the top causal factors leading to undesirable events as well as determine their impact on undesired events due to changes in the likelihood of the occurrence of the causal factors. Specifically, the model can be used for:

- Identifying top causal factors according to the highest changes of probability measure as a result of partial evidences on the target events

- Measuring the significance of the relationships of aggregated top causal factors with the undesired event overtime using time series and regression analysis
- Determining correlations between top causal factors to identify sub-factors for those factors that are difficult to act upon
- Identifying top generic issues in the NAS by applying a ranking algorithm that uses the frequency of each top causal factor and the severity index of events

This powerful tool can be used to supplement the existing decision-making process which relies on expert judgments that are used by governments to determining the initiatives to address safety concerns. Application of this methodology is used to identify significant causal factors and top issues in the NAS using 41,000 records of data from the ATSAP database from 2008 to 2013.

As demonstrated in one of the top causal factors models in this dissertation, the probabilistic causal models can be extended into decision networks by formulating a unified utility function using control and mitigation variables and by maximizing the utility function. A decision network is used to help make optimum data-driven decisions thereby reducing the likelihood of the undesired events and their consequences. This is achieved by combining graphical, computational, and statistical software libraries and packages.

The model outputs of the top causal factors for individual events show that 15 of the 21undesired events can be explained with a small number of causal factors, typically ranging from 5 to 8 sub-factors. This is in line with the yearly published report by the

“Top-5 Safety Hazard” provided by the Office of Safety at the Federal Aviation Administration (FAA). The top issues identified in the analysis are ranked by weighting the relative frequency of each factor and the severity of the events the factor is involved in. The top five issues of this research’s output include individual factors (controller actions), outside influences (distractions), clearance problems, aircraft performance, and procedure deficiencies. Only procedural deficiencies (conflicting) and clearance problems (heading) were reported in the Top-5 report for the year 2013. The other issues either were not identified in the manual process or were considered non-actionable (e.g. distractions). The analysis identified actionable sub-factors contributing to the non-actionable causal factors (e.g. ambient noise is one of the highly correlated actionable sub-factors identified for distractions). The analysis also identified the relationships between top factors and relative frequencies of the undesired events and trends overtime emphasizing the need for more careful analysis within the annual time frames as well as year-over-year analysis.

1. INTRODUCTION

Probabilistic causal models, also called Bayesian networks, are used in a wide variety of problem domains such as medicine, finance, forensic, computing, natural sciences, engineering, and many more. The principle of Bayesian networks is based on simple graph theory and rules of probability to represent random variables and probability distributions. Bayesian networks provide a natural and compact representation of probabilities by taking advantage of independencies that may exist in any problem with uncertainty. The random variables are represented by the nodes in the graph and the correlations and dependence of the variables are represented by the edges and local distributions on each variable. Building Bayesian networks for problems involving smaller number of variables is relatively simple and there are various commercial and open source packages that are easy to use. However, problems with large number of variables usually involve complex structures as well as large number of parameters.

1.1. Background of the Problem

Safety is a vital component of aviation operation and the very survival of the industry is entirely dependent on the safety of commercial aviation in transporting people and goods. Few issues grab the attention of the general public and elected officials as aviation accidents. The National Transportation Safety Board (NTSB) defines aviation accident as an occurrence associated with the operation of an aircraft that takes place between the time any person boards the aircraft with the intention of flight and the time all such persons have disembarked, and in which any person suffers a fatal or serious injury or the aircraft receives substantial damage.

Overall, the safety record of aviation has improved dramatically in the past many decades, and as a result accidents occur very rarely. However, aviation operation is not completely accident-free, and with the expected growth of flight operations in the coming decades, the system will benefit from improved safety procedures. One of the ways of improving aviation safety is learning from past mistakes, causes that led to accidents. But with such small accident rates it is practically impossible to rely on the lessons learned from past accidents to identify all possible causal factors in future potentially catastrophic accidents. It is also not an optimal approach to wait for accidents to establish enough data in order to prevent them in the future. Hence, since the 1970s, the aviation community has resorted to study the causal factors of incidents and improve the system based on the deficiencies discovered by incidents that could have become accidents with the existence of additional factors. Most aviation operators have some kind of safety action program through which they collect incidents from pilots, flight attendants, and maintenance personnel for analyzing events that have the potential to lead to accidents. According to International Civil Aviation Organization's (ICAO) recommendation, safety reporting is a critical component of Safety Management System (SMS). Most of these individual safety action programs share information and have created a central data repository which facilitate the environment to discover deficiencies in the system and make forecasts about potentially serious accidents.

1.2. Air Traffic Safety Action Program (ATSAP) Data

In late 2008 the FAA started ATSAP for air traffic controllers modeled after the Aviation Safety Action Program (ASAP) run by many airlines for pilots, mechanics, flight attendants, and dispatchers. The main objective of the program is to identify risks in the National Airspace System (NAS) and mitigate those risks by addressing issues that are relatively easier to fix in short time and collect historical data to be able to identify systemic and serious issues that could result in catastrophic accidents in the long term. ATSAP data is stored in a relational database and is comprised of structured data and narratives. The narratives provide descriptions of events by reporters and the structured data contain information about various categories, like event classifications, flight phases, complexities etc. and factors that caused and/or contributed to the incident.

At the top layer of the ATSAP causal hierarchical structure there are fifteen categories and each category is comprised of multiple level causal taxonomies. Each of these causal entries is used to measure its causality or contribution to various undesired events. The top causal factor categories are, 1) Individual Factors, 2) Supervisory and Organizational Factors, 3) Fatigue, 4) ATC/Pilot Communication, 5) Coordination, 6) Airspace and Procedures , 7) Aircraft Performance or Pilot Actions, 8) Weather, 9) Sector, Position and Environment, 10) Equipment, 11) Training and Experience, 12) Flight Data, Display Problems, and Aircraft Observation, 13) Airport and Surface, 14) Emergency Situations and Special Events, and 15) Traffic Management.

Events that are captured as involving loss of separation or Traffic Proximity issues are subdivided into, 1) Adjacent Airspace, 2) IFR to IFR (Instrument Flight Rules), 3) NMAC (Near-Mid Air Collision), 4) Runway Incursion, 5) TCAS RA (Traffic

Collision Avoidance System – Resolution Advisory), 6) Terrain/Obstruction, 7) VFR (Visual Flight Rules) to IFR, 8) VFR to VFR, 9) Vehicle/Pedestrian, and 10) Wake Turbulence. Events that occur as a result of unexpected conditions are subdivided into, 1) Aircraft Emergency, 2) Aircraft Security, 3) Altitude, 4) Course/Routing, 5) Equipment Issues, 6) Go Around, 7) NORDO (No Radio), 8) Speed, 9) Spillout/Whiskey Alert, and 10) Unsafe Situation. The severity, traffic complexity and other miscellaneous variables capture various aspects of incidents. Most of the variables in ATSAP database are categorical and hence they are more appropriate to classification algorithms such as Bayesian networks.

There are primarily two types of problems reported by air traffic controllers, systemic issues and safety events. Systemic issues are those that cause recurring problems that affect the NAS such as procedures, rules, equipment, practices, conditions, airspace design, etc. Incident reports on the other hand are filed for problems involving one particular event or incident such as possible or actual Operational Error, Operational Deviation, Pilot Deviation, etc. NTSB defines an incident as an occurrence, other than an accident, associated with the operations of an aircraft which affects or could affect the safety of operation. In loose definition, incidents are events as near-accidents and hence, causal factors that lead to incidents lead to accidents as well. Consequently, analyzing large number factors that lead to incidents helps to identify safety trends and proactively take accident preventive measures.

When controllers file incident reports, analysts work on those reports to gather additional relevant facts about the event either from the original submitter or external sources for known reports. Once the analysis part is complete, issues that can be addressed in shorter time period are resolved and the applicable causal factors are selected for the report and archived in the database. A number of variables can be selected as causal and/or contributing factors from multiple categories. For instance, an incident can be caused by a combination of weather factors, communication problems, and coordination problems; hence there exist relationships among various categories of causal factors.

1.3. Research Scope

There are various data-driven approaches to study causal factors for different accident scenarios and their consequences which include event sequence diagrams, fault trees, event trees, etc. This research focuses on the large number of potential causal factors for various unwanted events in ATC operation. As there are highly interrelated causal factors for various event types, there exists inherent uncertainty which can be represented using probabilistic relationships among the variables.

1.3.1. Research Components

This research contains various independent and related components (figure-1). The problem is defined based on the high number of factors causing and/or contributing to various aviation events in the ATSAP dataset. The large number of factors is abstracted using multiple levels of hierarchical structure using ATSAP taxonomy. In the first step, a complete hierarchical probabilistic model represents all the causal factors and events in the domain. The complete model answers two basic queries, the probability of each event and the contribution of all factors and their high-level categories. However, the complete model is a complex model, and hence, inference using Bayesian networks reasoning by providing partial evidences is nearly impossible. The need for simplifying the complex model leads to the core component of this dissertation research which is the identification of the top causal factors for each event. Top factors component includes functionalities to identify most relevant causal factors and discover the correlation between the factors for each event type. This primary component includes other sub-components to answer related questions to the top factors: 1) Top generic issues, 2) Time-based relationships, and 3) Factor associations. This section provides the high level overview of each component.

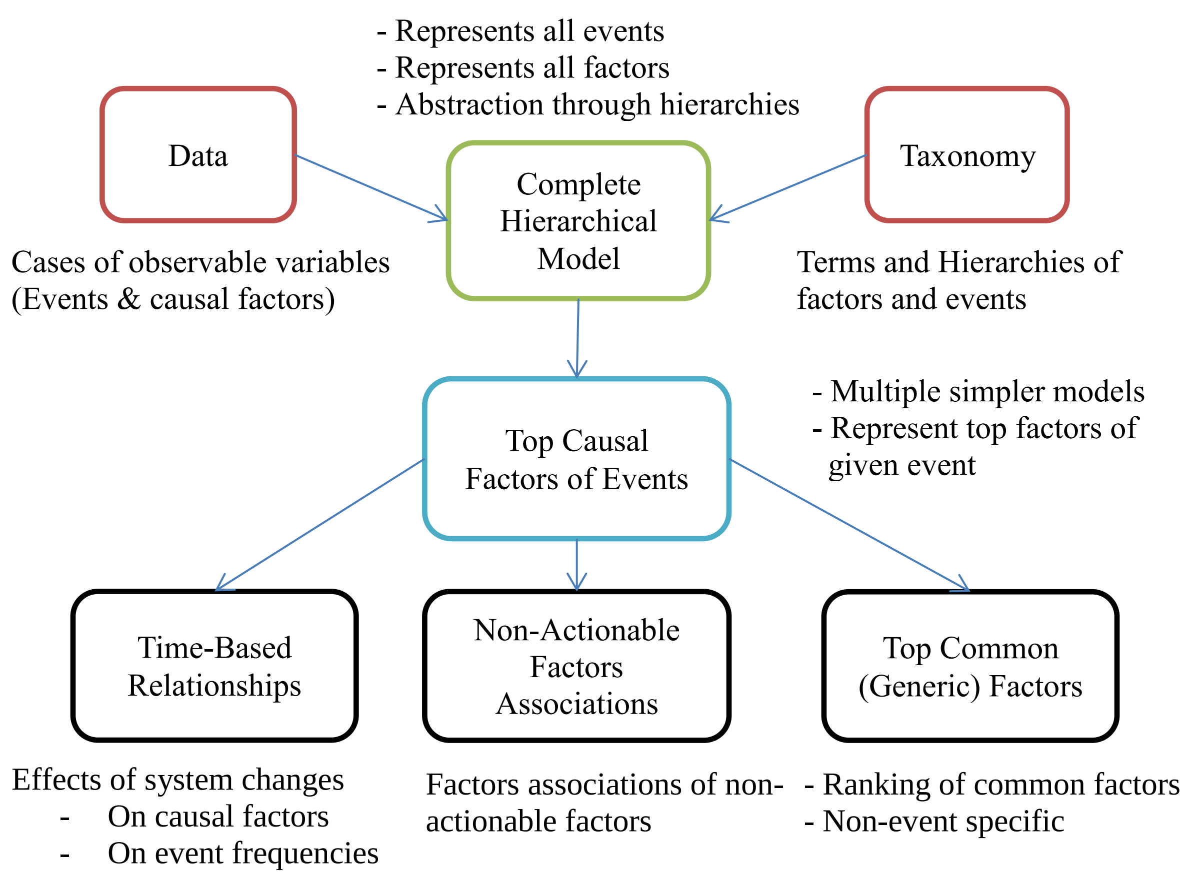


Figure 1: Research Components

1.3.2. Hierarchical Abstraction of Causal Factors

In many domains with large number of variables people often use categories and hierarchies to study relationships by abstracting low level details. Similarly, to simplify modeling safety risk in the NAS, we need categorical abstractions to analyze the large volumes of causal factors of ATC-related aviation incidents. This research incorporates the various level categories as defined in the data dictionary of the dataset to abstract causal factors. The abstraction layers help study factors at higher levels which become necessary often times when we don't need to pay close attention to the details. For instance, one may need to study the effect of aircraft performance in general in causing wake turbulence events without going to the details of specific performance related issues of different aircraft types.

1.3.3. Top Causal Factors of Events

At the core of most aviation safety risk analysis is the identification of the causal and/or contributing factors of incidents that could potentially lead to accidents. As a complex system the NAS is exposed to various types of events that result in undesired outcomes. This research focuses on events and causal factors that are strictly related to ATC operation. Hence, a critical component of the research is to identify the top causal and/or contributing factors of each ATC event from data. In ATSAP dataset there are more than three hundred causal factors that play a significant role in causing ATC related aviation events. However, for the purpose of safety assessment, it is nearly impossible to focus on all these factors. So, the goal of this part of the research is to algorithmically determine the causal factors that are responsible for the majority of individual events. By isolating the factors that are primary contributors to safety issues, it becomes possible to focus on smaller but critical issues that can be studied and addressed reasonably efficiently with the limited resources available. The methodologies section will cover the details of the algorithm as to how the top factors are selected.

1.3.4. Common/Generic Safety Factors

Isolating the causal factors of individual events are important in a sense that occasionally, we focus on specific aviation events such as loss of separation, runway incursion, operation deviation etc. to study them in detail and understand why they occur. However, the primary goal of safety management is to minimize the risk in the NAS from any kind of potential aviation accident. So, the study of generic aviation issues, regardless of what type of event they are likely to lead to, is a critical piece of safety assessment. The Air Traffic Organization (ATO) office of safety at the FAA has a program called Top-5 Hazard that is responsible to publish the five significant ATC related issues every year. Although some of the methods followed in the identification process are not backed by sound mathematical approaches, the fact that there is a responsible and dedicated party to isolate those few issues is critical. This research introduces an algorithm that ranks the top causal factors identified for all ATC events into generic ATC related factors based on the relative frequency and the severity classification of every event that the factors are associated with.

1.3.5. Relationships of Causal Factors

At times, we need to deal with factors that are highly impactful in causing events but are difficult or impossible to directly tackle. A real example of such issues is a duty related distraction, which according to the result of this research is the fifth top issue in causing various ATC related aviation events in the last two years. However, there is little one can do to directly affect the impact of duty related distraction issues. So, the approach introduced in this research is to treat such factors individually as target variables and explore other causal factors that have significant correlation with them. The intuition is by acting on other strongly correlated factors the effect of the target causal factor can be reduced thereby minimizing the likelihood of those events that are caused by non-actionable factors.

1.3.6. Decision Analysis

Incorporating a decision optimization mechanism to a safety risk assessment is an important component and adds another layer of analysis to the factor identification process to make a better decision on the outcome of the probabilistic models. The ultimate goal of identification of issues and causal factors is to intervene in the system by taking actions to change the natural course of events, that is, to minimize the probability of the occurrence of undesired outcomes in the NAS. However, the mere identification process doesn't give us the means by which we make the optimum decisions. It doesn't answer questions like which factors to resolve first, how many factors to deal with, and which combinations of fixes give rise to the optimum result, both in terms of safety impact and resource allocation. Decision analysis will enable us to efficiently pick the right issues to work on with the amount of resources we have. In this research, I demonstrate a decision network based on three top causal factors of a runway incursion problem. There are some assumptions that I make since some of the data points required for such analysis is not available in the dataset used for this research.

1.3.7. Summary of Research

The list in table-1 below summarizes the existing challenges and the solutions suggested in this research to each problem.

Table 1: Summary of Research

Item	Problem	Solution
1	As attributes of a complex system, the causal factors of aviation events are abstracted through hierarchies and categories. How do you represent such abstractions in probabilistic models?	Represent the categories as regular variables and encode them in the models and calculate their probabilities from their low level counterparts which are directly observable.
2	Of the large number of attributes in the NAS, what are the top factors that are causal and/or contributory to various aviation events?	Identify small number of top causal factors that are responsible for the large majority of events using a probabilistic approach.
3	The ultimate goal of aviation safety is to make the NAS a safer system, not studying individual events. What are the top common issues in the NAS regardless of their association to various event types?	Using the top causal factors identified for various events, apply a ranking algorithm based on frequency and severity in order to determine the contribution of factors in causing events.
4	The NAS is a dynamic environment, hence, factors affecting its operation change over time. How do you determine the change of the effect of some factors on events over a period of time?	For factors and issues identified as causal and/or contributory for various events, calculate the relationship of their aggregates with the frequency of the target event and determine their impact overtime.
3	Some factors are non-actionable, that is, no direct resolution is available. How do you approach such issues?	Treat them as target variables and identify other causal factors that have strong correlations. By resolving those factors it is more likely the target factors are affected indirectly.
6	Probabilistic modeling for complex system is difficult in general, even with the help of software packages. Can the process be fully automated?	Design an automation program that represent various parameters and build models with little manual intervention by merging various packages and custom code

1.4. Why Probabilistic Reasoning?

Until recent decades, the Artificial Intelligence (AI) community had not embraced probabilistic reasoning as a paradigm to deal with problems involving uncertain set of evidences or incomplete information. The driving theme in the 1960s and 1970s in most AI projects was that logic can fully represent knowledge and the reasoning within. However, most expert systems needed a mechanism to deal with the inherent uncertainty that results from ambiguous concepts and/or simple lack of complete evidence which may not be represented fully with logic. With the advent of naïve Bayes in medical diagnosis, it became possible to encode probability in AI programming although the strong assumption of independence extremely limited the scope of applying naïve Bayes in many complex problems. As computational power increased significantly it was possible to represent uncertainty with probability without the constraints of strong independence assumptions. Bayesian networks are one of such systems to encode uncertainty in many problem domains, they are representations of the probabilistic relationships among a set of variables, and they have gotten a wide acceptance in the larger AI community.

The application of probabilistic reasoning as a classification and predictive modeling tool may be dictated by various requirements and objectives in the domain. In general probabilistic reasoning using graphical models provides the encoding of uncertainties using probabilities and the compact representation of complex joint distributions. This section summarizes the benefits of applying probabilistic reasoning for modeling aviation risk and analyzing incidents data.

1.4.1. Role of Uncertainty

In any given domain with some level of complexities, there are many sources of uncertainties, the complex interaction of observable and unobservable variables, ambiguous concepts, lack of knowledge in some areas, human subjectivity, and the limitation of our models. So, most models representing a real world scenario have to deal with uncertainties to various degrees. As this research project focuses on one of the most complex systems available, it deals with uncertainty in a number of areas. Modeling the ATC-related aspects of the NAS involves various level of uncertainties based the specific area of application such as the interaction of causal factors, the severity of events, the dynamic nature of the NAS etc. Therefore, probabilistic reasoning is the most appropriate analytical approach to assess and represent those uncertain relationships among various components.

1.4.2. Compact Representation of Complex Structure

At the very basic level, a probabilistic model is about compact representation of joint distributions. The complexity of modeling joint distribution increases exponentially with the number of variables. Assumption of absolute independence among all variables makes the space and time complexity easier to deal with, but such strong assumptions are rarely satisfied for any real world problem and not suitable in most cases. The alternative is a relative independence assumption by involving conditional probability. Applying such weaker assumptions, probabilistic models can represent the full joint distribution of most real world problems compactly with reasonable accuracy. Air traffic operation in the NAS involves many variables, and without some level of independence assumptions, it is extremely difficult to model the full joint distribution.

1.4.3. Extension to Decision Networks

Probabilistic graphical tools are used to model either simple correlations or causations and make probabilistic inference using the knowledge base in the model. However, standard Bayesian networks cannot be used for decision analysis. A decision network is a generalization of a Bayesian network by incorporating one or more expected utility functions. By maximizing expected utility functions, a decision network becomes a natural extension of Bayesian networks and can be used to help make optimum decisions. Many of the challenges in ATC operations involve making decisions to make changes to existing systems and introducing new technological solutions, procedural, and/or policy changes with minimum disruption to the system as a whole. By extending the various probabilistic causal model outputs in this research to decision networks in future work, critical decision making processes can be enhanced following a data-driven approach.

1.5. Application in Other Domains

The methodologies used and the approaches introduced in this dissertation are applied on aviation incident data as a research case study. However, they can equally be applied for problems in other domains that have similar characteristics. The core of this research is the introduction of a feature selection algorithm using a Bayesian network principle iteratively. Specifically, a smaller subset of features (causal factors) is selected for each event type of ATC-related aviation incidents from a large set of factors. The purpose of the feature selection algorithm in this research is simplifying the problem by reducing the dimension and improving the prediction performance of the classification of the target variables. Although the features selected in the case study for this research involve only causal factors, the algorithm can equally work for non-causal predictors.

As described in section 3.3, the two-phased selection algorithm introduced in this research include independent ranking of the factors followed by a selection process using evidence propagation of Bayesian networks. The first step involves ranking all the available features using a sensitivity analysis based on the difference of prior and posterior probabilities. In the second phase, multiple Bayesian networks with increasing number of features are created iteratively and the process stops when the gain in the reduction of the Brier score, a probabilistic prediction metric, is smaller than the gain in the previous iteration. The final probabilistic network will contain only the significant features for classifying or predicting the target variable. In this approach, the ranking phase is an independent preprocessing step for filtering the large number of features. Hence, it is a step that ranks features according to their individual predictive power based on conditional probability. Due to its individual treatment, this approach may be prone to selecting redundant features.

For relevant feature F_i, other feature $C_{i,}$ and target event E_i, the following probability relation holds.

$$P(E_i|F_i, C_i) \neq P(E|C_i)$$

One area in healthcare domain where this selection algorithm can be used is for diagnosis of a disease. A set of test cases may be used to select features that can predict the existence of a heart disease, for instance. The factors in such kind of feature selection may or may not be causal factors as their type is irrelevant for the mere purpose of predicting the disease. To select a subset of factors from a large set that can be used to diagnose a heart disease, in the first step, all the causal factors are ranked independently using the difference of the prior and posterior probabilities. In the second phase, multiple Bayesian networks are learned incrementally by including factors to the probabilistic network, one at a time, according to their rank until the gain in the reduction of the Brier Score (BS), a probabilistic accuracy metric, starts decreasing. When the current BS reduction gain is smaller than the one in the previous iteration, the probabilistic network learning process is stopped and the factors that have become part of the structure in the network are the relevant factors that can be used to diagnose the disease.

All the other algorithms that are part of this research are based on the core selection algorithm, i.e. they are extensions of the identification of the significant factors. The generic top factors, (section 3.5), are the re-ranking of all the selected factors based on frequency and severity index. As a result, they can be used in other domains as well, for instance, significant factor for cancer as opposed to a specific type of cancer (e.g. prostate cancer). Similarly, the time-based relationships, (section 3.6), can be applied in any problem with a dynamic environment in which there is a potential for relationship changes as a function of other external factors.

2. LITERATURE REVIEW

Many data-driven research projects involve some level of modeling, usually based on statistical principles. Similarly, safety risk analyses in general are mostly done with the help of models. Graphical models have the added benefits of presenting the output using visualization tools that can appeal to the human eye. Although there are various graphical tools for the aviation safety professional, Bayesian networks for risk analysis are becoming popular. However, most Bayesian modeling in aviation risk analysis are done using expert judgment due to immaturity of model learning algorithms and data availability. Some graphical tools in use today and few of the data-driven research works that have some resemblance to this research project are explained in this section.

2.1. Common Models and Tools in Aviation Risk Analysis

Aviation operation is realized by the complex interactions of technical and organizational systems which also contribute to the failure of this operation at times. Hence, models to represent such systems need to simulate the complexity of those interactions. There are various visual or graphical models that are widely used in aviation risk analysis. Each has strengths and weaknesses and is applied in different scenarios of risk assessment and visualization of safety hazards. Below is a short survey of the models and visual tools that are commonly used in aviation safety analysis.

2.1.1. Heinrich Pyramid

In his book titled “Industrial Accident Prevention: A Scientific Approach”, (Heinrich, 1931), Herbert Heinrich explains the effect of workspace safety on industrial accidents. His empirical finding called Heinrich law asserts that “in a workplace, for every accident that causes a major injury, there are 29 accidents that cause minor injuries and 300 accidents that cause no injuries.” It is usually represented as a pyramid. He argues that the unsafe acts of people are responsible for the majority of accidents, 88 percent based on his empirical result. The law suggests that by addressing most commonly occurred unsafe acts and minor incidents, fatal accidents can be prevented. Many safety professionals are critical of his findings and contend that it is no longer valid for evaluations of safety risks. Most safety analysts believe that it is not necessarily true that by eliminating minor unsafe practices it is possible to prevent accidents. However, the justification for studying aviation incidents to prevent accidents is still largely based on the premise of Heinrich’s law.

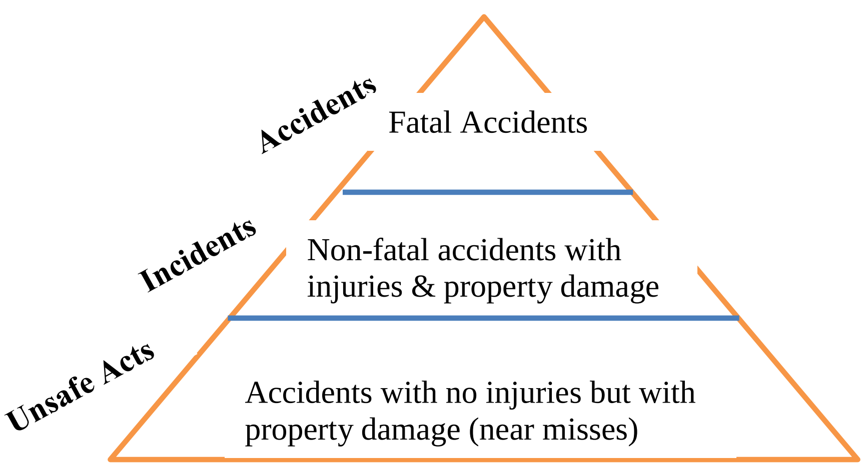


Figure 2: Heinrich Pyramid

Also, contrary to the law’s implication that unsafe acts are results of human errors, it is widely accepted that system designs and other environmental variables are more responsible for unsafe acts in the workplace.

2.1.2. Reason Swiss Cheese Model

The other commonly applied and less controversial risk analysis model is the Swiss Cheese Model (Reason, 1990), which stacks multiple causations of accidents as slices of Swiss cheese. In this model, the hypothesis is that primarily four levels of failure – organizational influences, unsafe supervision, preconditions for unsafe acts, and the actual unsafe acts are the root causes of most accidents. Each slice can be considered as a defense layer to accidents, and holes of various sizes at each layer represent weaknesses of that layer. The system as a whole fails and results in accidents only when all the individual components fail which happens when the holes at each layer align.

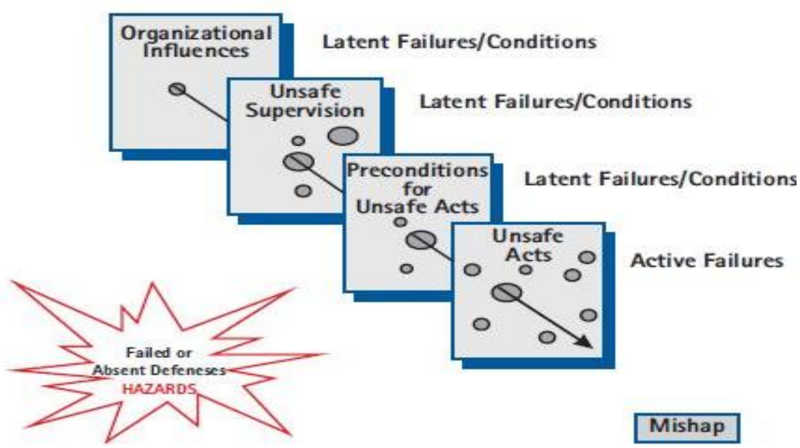


Figure 3: Reason's Swiss Cheese Model [Adapted from Reason, 1990]

The first three layers in this model are known as latent failures which are contributory factors and the failures at the last layer of defense is called active failure and is the result of unsafe acts by human actors that can be directly linked to an accident.

One obvious limitations of this model is that it doesn't look at the interactions among the four levels; instead it models the barrier at each layer and their weaknesses without regard to the possible effect of one layer on the other.

2.1.3. Event Sequence Diagram (ESD)

ESD is a flowchart with paths leading to different end states for modeling possible risk scenarios. It is used to visualize the logical and temporal sequence of causal factors leading to different types of failures. Various graphical symbols are used to represent elements and conditions of the event sequence. In the simple ESD below, the initiating event is represented with an ellipse and the possible conditions that follow the event are symbolized using rectangles in a logical order. The next possible sequences of events are shown as diamonds representing the end states of the sequence.

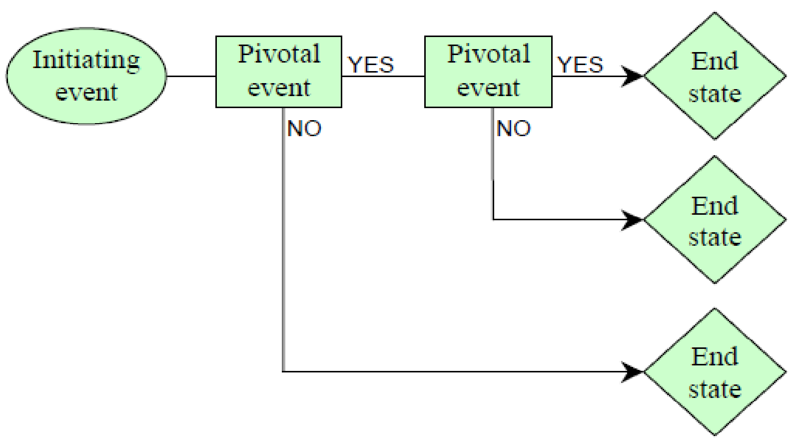


Figure 4: A Generic Event Sequence Diagram [source: CATS, 2006]

2.1.4. Fault Trees

Fault trees are representations of accidents as a result of system failures becoming causal factors due to the relationships between components of systems and sub-systems.

The basic events are the failure of components connected by logical gates (AND, OR, NOT) giving rise to the top event. As a result, analysis based on Fault Trees involves quantifying the propagation of risk events to cause accidents or hazards. In a fault tree the primary events are placed at the bottom of the tree and the top event is the hazard, usually representing the system failure as a consequence of the combination of the primary events.

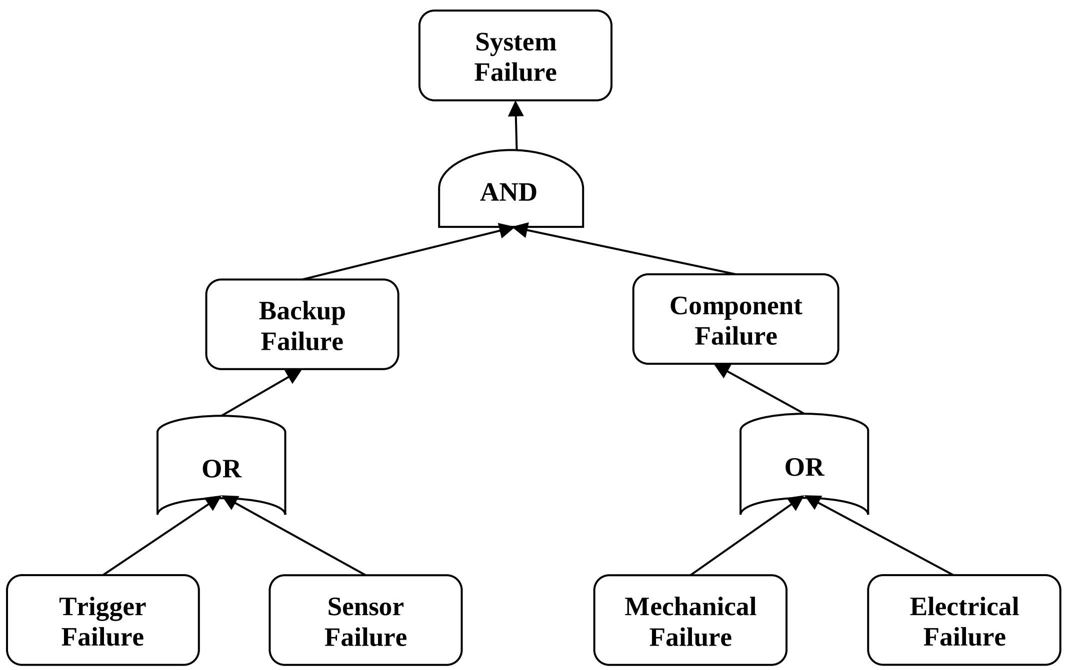


Figure 5: Fault Tree using Logic Gates [Adapted from Fenton & Neil, 2012]

2.1.5. Bow-Tie

Bow-Tie is a hazard identification approach by combining causal models (fault trees) and consequence models (event trees). Accidents are mostly the result of hazards and the presence of one or more events; hence hazard identification is critical in risk assessment. In Bow-Tie, the hazard is represented at the center by the “knot” in the bow.

The left part of the bow-tie is effectively a fault tree displaying the causal interaction that leads to the hazard. The right part models the consequences of the hazard, which is represented by event tree.

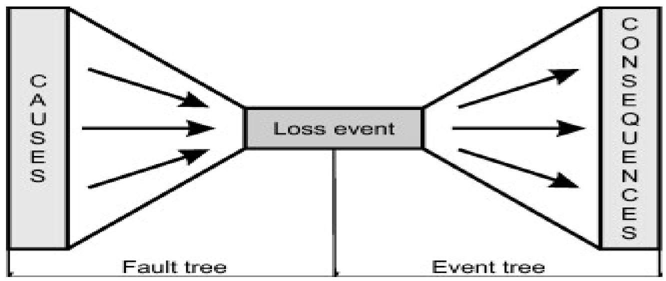


Figure 6: Bow-Tie Diagram

2.1.6. Risk Matrix

Risk matrix is a graphical tool to depict the encoding of probability and severity of the outcome of a hazard; it is used to determine safety risk levels. The columns in the matrix indicate severity categories and the rows reflect the likelihood categories.

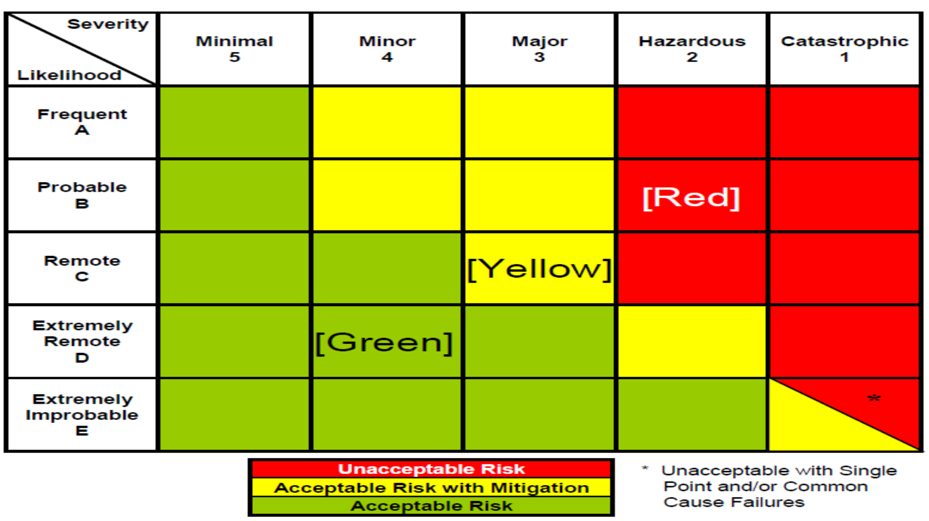


Figure 7: Risk Matrix [Adapted from FAA Order 8040.4A]

Risk matrix is a simple visualization tool to communicate safety risk using standardized baseline for a specific industry. The level of the risk can be quantified statistically as the product of the probability of the hazard and the severity of its outcome. Figure-7 is the risk matrix used to assess safety risk in Safety Risk Management (SRM) process at the FAA's Office of Safety.

2.2. Data-Driven Researches

The impressive record of aviation safety is achieved through the collective work of many researchers and the implementation of their research results by various industry players and regulators. There is a large body of aviation safety risk researches that are too many to list in this dissertation. I have provided a short list of data-driven research works that primarily focus on the study of incidents, accidents, causal factors, and their correlations and apply different approaches to quantify the associated risk.

2.2.1. Causal Model for Air Transport Safety

The CATS model is a scientific framework realized by the work of multi-disciplinary consortium of experts and organizations and was conducted under the supervision of Delft University in the Netherlands. It is a product of a research project that took three years to finalize, and the team was comprised of mathematicians, computer programmers, data analysts, and aeronautics experts. The CATS research was mandated by the Dutch Parliament in 2001 to create a causal model that focuses both on internal and external safety factors to aviation, but due to the difficulty of incorporating all external factors, amendment was done in 2004 to focus primarily on the internal factors in aviation.

One of the justifications for causal models, the researchers argue, is that traditional analytical methods are no longer able to deal with systems whose degree of complexity are at the level of aviation's. The CATS model provides the capabilities to get into the cause-effect relationships of incidents and accidents and enables risk assessment quantitatively as well as the mechanism to measure mitigation of risk.

2.2.1.1. Overview

Different categories of aviation accidents are direct consequences of the complex interactions of various causal factors the severity of which depend on the specific phase of flight in which they occur. The CATS project approaches this complexity based on the accident categories in different flight phases by representing them in separate Event Sequence Diagrams and Fault Trees and converting the individual models into one integrated Bayesian Belief Network (BBN). As a result, the CATS model can deal with causal factors as well as consequences of accidents, but the authors suggest giving emphasis on the causal factors, hence the name. Unlike fault trees and event trees which are inherently deterministic, the final output of CATS model, as a BBN-represented mathematical tool, is the probability of an accident as calculated from the various probabilistic relationships of the causal factors. The causal factors include interactions between systems and people who operate and maintain the systems: controllers, pilots, and maintenance personnel.

2.2.1.2. Data and Expert Judgment

The researchers have used both data, when available, and expert judgment to build the CATS model. They primarily used ICAO's Accident/Incident Data Reporting

System (ADREP) database whose main sources are airlines and airports of member states and Airclaims which is a data source of aviation claims. They also used Line Operations Safety Audit (LOSA) data, which are data collected from a voluntary formal process that uses trained observers to collect safety-related information on regular basis to establish performance of cockpit crews.

2.2.1.3. Methodology

The CATS model consists of a number of programs, UNINET, a Bayesian software package to perform mathematical operations in the quantification process, UNISENS, to perform statistical analyses, UNIGRAPH, to display the BBN, and database management tools. The CATS research project was built upon a previous research work done in the area of occupational safety, associating technological risks to management influences. The product of this work is a model comprising of three modeling techniques, Event Sequence Diagrams (ESD), Fault Trees (FT), and Bayesian Belief Nets (BBN). The ESDs are used to model the various potential accident categories along with their causal factors using the taxonomy adopted in ADREP. The ESDs are divided according to flight phases such as Taxi, Take-Off, Climb, en route, and Approach and Landing. In the final CATS model 33 ESDs are incorporated.

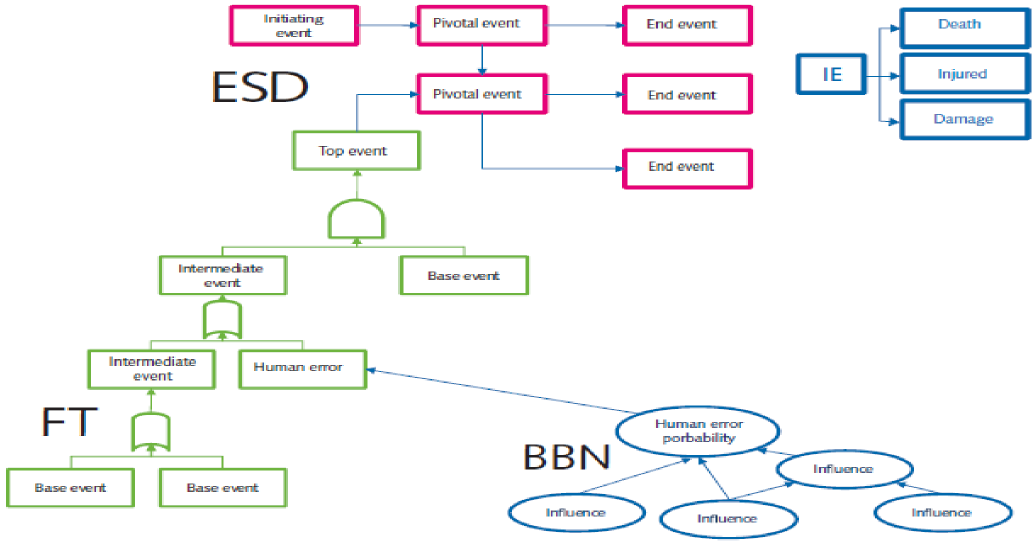


Figure 8: The Basic Components of the CATS Model [source: Dierikx, 2009]

The CATS model also incorporated Fault Trees which existed for each initiating event in the ESDs. Accident descriptions from historical data were used to identify events and their causal factors and as the basis for quantification in constructing the fault trees. Due to the limitations of the ADREP accident causal data for quantifying the fault trees, the researchers also included data from accident investigation reports, incident reports, and other related sources when applicable. For ESDs with little or no accident data, the researchers primarily relied on precursor incidents to quantify the fault trees.

The third and probably the most critical component that is used for CATS design is the BBN of human performance model (HPM) which incorporates the probability of human error as accident causation. Human intervention is vital for any accident analysis, and the CATS model includes the three HPM models—crew, ATC controller, and maintenance technician built by various research groups. The three basic constituents of the CATS model are depicted in a single integrated model as shown in the figure-8 above.

2.2.1.4. CATS as Integrated BBN Model

The most important feature that makes the CATS model different and more powerful than other similar models is that the individual ESDs, FTs, and the BBN components are merged into one big integrated BBN model. This integration allows analysis of interdependencies in a consistent and convenient way. The individual components are still useful and self-sufficient for various studies. However, having those individual models integrated in such a way that technical failures and human behaviors are represented in a consistent manner makes the CATS model very powerful. According to one of the researcher in this project, "*CATS is the second best representation of reality, reality being the best.*"

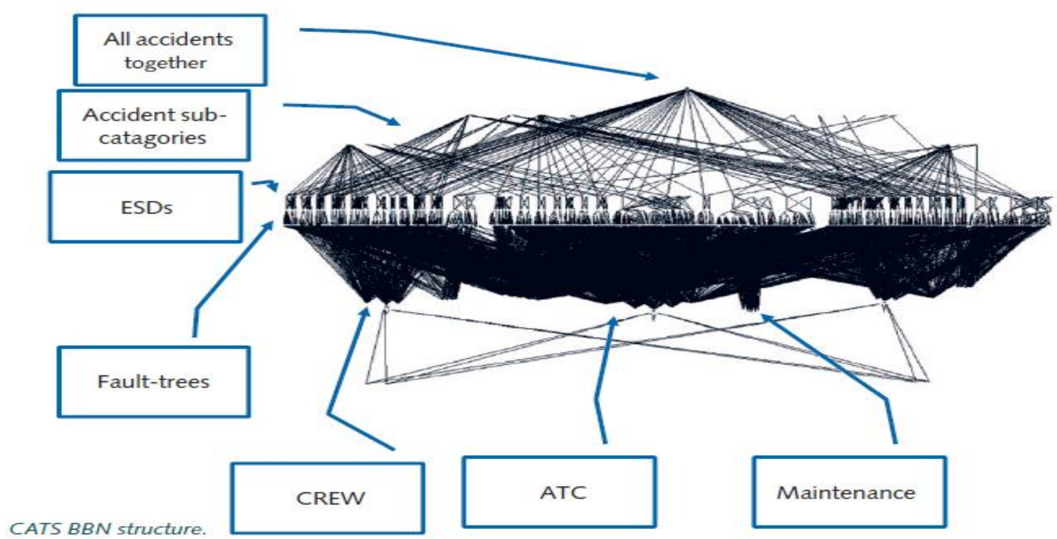


Figure 9: The CATS BBN Structure [source: Dierikx, 2009]

As described above, the final outcome of the CATS model is the probability of an accident as a result of the interaction between various components. The final model has 1400 nodes and 5000 arcs representing 33 accident scenarios and 1200 initial and intermediate events associated with these accidents, the network is shown in figure-9. The reader is referred to the CATS report to fully understand the principles of the conversion process and the detail mathematical operations the research team followed to quantify risk in various accident categories.

2.2.1.5. Observation

The main strength of the CATS model is the integration of various dependencies of causal and contributing factors to measure probability of accidents which makes it closer to reality. The model makes it possible to investigate various scenarios by varying parameters that maybe difficult in real life. The research team of the CATS model relied heavily on expert judgment to quantify the human performance model, so one needs to exercise caution when analyzing the human error aspect of safety risk using this model. For instance, maintenance crew's model is equally represented in the model as flight-crews and air traffic controllers, but in reality the maintenance technician can, for the most part, affect accidents indirectly. One important improvement that can be done in CATS model, especially in areas where experiment judgment is heavily used, is to do validation work by finding related data or simulated data or apply part of the model in other industries where data can be found relatively easily.

2.2.2. Modeling Aviation Risk (ASRM)

ASRM is a product as well as a process; it is developed with joint support from the National Aeronautics and Space Administration (NASA) and the FAA and primarily intended for “low probability-high consequence (LP/HC)” events. LP/HC events are characterized by consequences of low likelihoods, high severity and they are ill-structured and result from multi-layered causal and contributing factors. Due to the limitations of common analytical risk methods, such as fault trees, event trees, event sequence diagrams, the team designed Bayesian Network-based solution that enables to analyze multiple causalities in an integrated and systematic fashion. Using this approach the authors claim that precursors to aviation incidents can be identified.

2.2.2.1. Methodology

As a Bayesian approach, the authors represent precursors as nodes and the arcs represent the relationships between causal factors. Interventions in the form of technology are represented by decision nodes. The authors used the Hugin Bayesian networks inference algorithm and programming tool.

So as to measure aviation accident risk, ASRM aggregates ideas and concepts regarding aircraft accident causal and contributing factors. As a process, ASRM lays out procedures as to how multi-layered precursors can be studied together along with interventions to assess their effects in causing accidents. As a product, multiple ASRM models were developed based on cases of specific aviation accidents. In these models, the probabilistic interdependencies of organizational, individual, task/environmental factors are analyzed in relation to aircraft accidents in a structured approach and risk assessments are performed by measuring the likelihood and severity of aviation accidents. A total of twenty models have been developed at Rutgers University as part of this project for six types of aircraft accidents, such as controlled flight into terrain, loss of control, runway incursion, engine failure, maintenance, and general aviation. The models were generated both using case studies and elicitation of expert opinions. Thirty subject matter experts participated for training the models. Below are the systematic steps the researchers followed to create the risk models for various accident types,

- Selecting and analyzing a real accident case
- Identifying the case-based causal factors
- Constructing the diagram of the causal factor correlations
- Building the Bayesian Believe Network (BBN)
- Inserting technologies/interventions
- Evaluating relative risk

ASRM researchers identified causal factors from accident reports and used the Human Factors Analysis and Classification System (HFACS) as developed by Weigmann and Shappell (2003). HFACS taxonomy follows the Reason (1995) accident causation framework, and primarily focuses on human and organizational error modeling. In addition, ASRM included operational and equipment factors when applicable for the accident type in the model.

After the correlation of the causal factors have been established, the conditional probability tables are populated from the “beliefs” of subject matter experts by establishing boundary conditions such as a towered airport, moderate traffic density, time period, etc. The Subject Matter Experts (SMEs) have also assessed the impact of one or more newly introduced technologies on the causal factors in the form of conditional probabilities.

2.2.2.2. Observation

A significant contribution of this research and the ASRM process is the assessment of relative safety risk. The software prototype from this research can be used to evaluate various technological solutions in reducing risk by affecting causal factors for any specific type of accident, which can serve as a decision making tool. One of the limitations of the ASRM process is that it follows a reactive approach; it identifies causal factors from actual accident. Also, similar to other Bayesian belief network solutions, it relies heavily on expert judgment to identify causal factors.

2.2.3. Relationships between Aircraft Accidents and Incidents

This is a research work done by Nazeri, Donohue, and Sherry in 2008 at George Mason University. In this research the authors employed a data mining technique to analyze factors (primary and contributory) that lead to incidents in relations to accidents. Accidents are occurrences associated with aircraft operations in which people suffer death or injury, and/or involved aircraft damage. Incidents are safety hazards which, with the presence of one or more factors, could have resulted in accidents. Accidents are rare events, and hence it is difficult to infer causal patterns from accidents alone. As a result most data-driven aviation safety researches should involve some form of incident analysis. Figure-8 shows annual rates of accidents which are filtered for this study based on the authors selection criteria (source of data: NTSB).

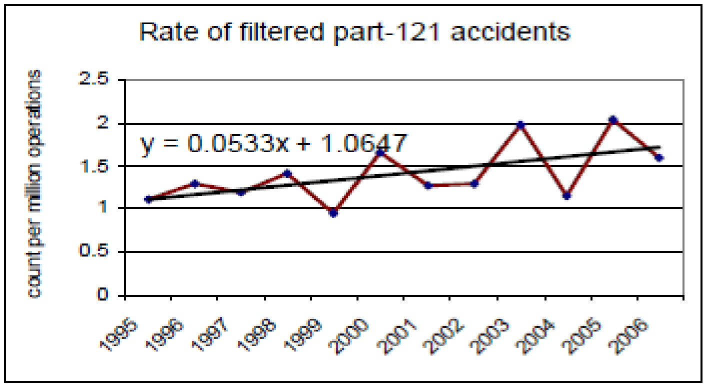


Figure 10: Rates of Part-121 Accidents that meet this Study's Filtering Criteria

As much as analyzing accident data alone have limitations due to the unavailability of statistically significant data, just relying on incident data without analyzing the relationships of their common factors could result to wrong conclusions. Two influential safety models referenced in this research and are widely accepted by the aviation community are Heinrich Pyramid by Herbert W. Heinrich (1931) and Swiss Cheese Model by Dante Orlandella and James T. Reason (1990).

Similar to the Heinrich pyramid, the authors in this research analyzed the relationships between incidents and accidents. However, they focused on the causal factors, more significantly of accidents, as opposed to a direct quantitative comparison.

2.2.3.1. Data Source

The data used for this research consist of accidents and incidents pertaining to commercial flights (1995-2004). The data sources are NTSB, Aviation Safety Reporting System (ASRS), Accident/Incident Data System (AIDS), Operational Error Data & Deviation (OED), and Service Difficulty Reports (SDRs). The two data types of reports are structured and event narratives. They filtered out events which are not direct results of the operation such as medical and alcohol related events, terrorism, bird strikes, and incidents during non-flight phases as well as incidents in the Alaska region. Some of the limitations in such sources of data are the potential bias from self-reporting and the underrepresentation caused by unreported events.

2.2.3.2. Methodology

The authors followed a three step process to identify causal factors that are common between accidents and incidents. First they followed a data-driven methodology to identify common factors and sorted them into a hierarchy of factors and sub-factors across the databases and represented them in vectors. The factors are Aircraft, Airport, Air Traffic Control, Company, Maintenance, Pilot, Weather, and Other. Each of the categories except "Other" has also multiple-sub categories.

Second they applied Search and Testing for Understandable Consistent Contrasts (STUCCO) algorithm to analyze the vectors of the common factors in incident and accident groups. STUCOO algorithm detects differences between contrasting groups automatically from data by seeking conjunctions of attributes and values that have different levels of support (frequency count) in multiple groups. The attributes-values pairs are used to indicate the presence or absence of factors in each event group. The support of the factor-set in each groups are used to calculate the deviation which in turn, based on the minimum threshold value of 1%, is used to proceed to the next step for further testing. Then the authors run Chi Square tests for significance of factor-set distribution over the two groups, a p-value of 0.05 is used as a threshold.

Finally, they ranked the significant factor-sets based on the Factor Support Ratio measure as follows.

$$Support\ Ratio = \frac{Support\ (accident)}{Support\ (incident)}$$

While the deviation measures the difference between the support of the factor-set in accident and incident groups, the support ratio measures the ratio of the probability of a factor-set being involved in accident to its probability in incident. As a result, the support ratio is used to compare the likelihood of a factor-set's involvement in accident and incident.

2.2.3.3. Results

The research shows that when factors co-occur they tend to result more in accidents based on the likelihood calculated from the support ratio. Company factors, which include mistakes by airlines personnel, non-optimal company procedures, lack of management etc., are identified as the highest ranked accident factors of all the factors considered in this research. ATC factors are the next highest ranked factors, communication issues, such as readback problem and exchange of traffic advisory and weather information, being the most common sub-factors. Pilot factors, of which visual lookout is the most frequent, are identified as most occurring both in accidents and incidents which decreases their overall support ratio. Aircraft factors, which primarily include the system of the aircraft and their performances, are identified as incident factors unless combined with other factors. The authors conclude that based on additional study of ten-year historical databases, pilot and aircraft factors are decreasing while ATC factors are on the rise. Based on such trend, projections of younger ATC workforce replacing exiting controllers, and the likelihood of ATC factors involvement in accidents in this research, they argue that there is the potential of accident increase unless additional measures are taken.

2.2.3.4. Observation

The research is a data-driven approach and follows a sound method involving statistical test. This study can serve as additional evidence as to the existence of relationships between factors involving incidents and that of accidents. The conclusion of this research is also similar to some other studies which investigated relationships between aviation incidents and accidents. Some of the limitations of the research as pointed out by the authors are, it didn't include some large and popular databases. For instance, ASAP is a program run by almost all commercial airlines and has a large data repository. Including ASAP data will definitely provide more insights about causal factor relationships. Also, due to the unavailability of data, this study is limited only to commercial flights even though most accidents occur in general aviation. Another limitation in this research is that causal factors are broadly categorized without regard to the type of incident/accident involved and the severity of the event which are two important parameters in order to use the relation of the causal factors to mitigate risk events.

2.2.4. Other Data-Driven Researches in Aviation Safety

Other researches that have some level of similarities in their objectives to this research, which is the analysis of incidents and accidents data to identify causal factors in order to determine the likelihood of the occurrence of future aviation accident, are as follows.

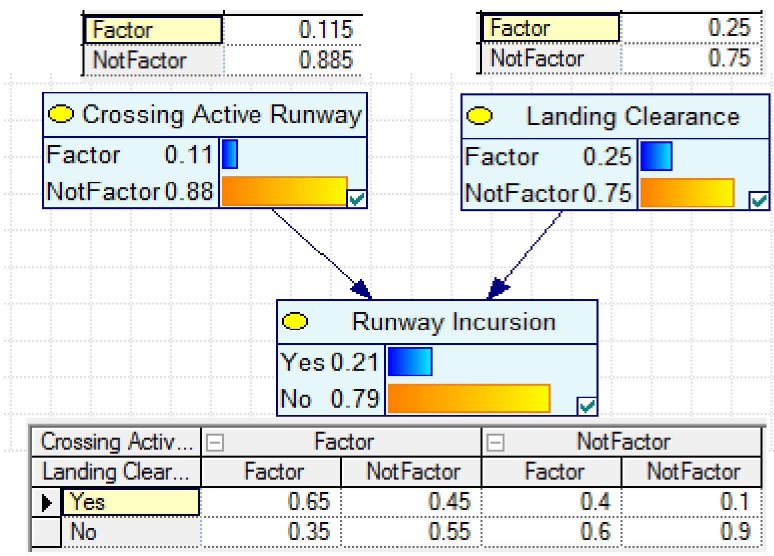
Nazeri (2007) identified the relationship between incidents and aircraft accidents through common causal factors based on cross-database analysis. Neil, Malcolm, & Shaw (2003) showed the process of constructing Bayesian Belief Networks for ATC operations ranging from airspace design to the operation of aircraft safety net features to a potential accident. Motevalli & Sakata (2005) enumerated all the milestone accidents in aviation safety from 1998 through 2020 which led to significant changes in technology, policy, and regulations as reactive solutions as opposed to a proactive one. Marsh & Bearfield (2007) demonstrated how to fully represent multiple quantitative risk models, such as fault trees, using Bayesian networks by applying a case-based approach. Kardes & Luxhøj applied hierarchical approach to Bayesian networks to model general aviation system risk. In this research, the authors provide a meaningful hierarchical representation of the Reason model, which contends that there exists interactions among individual factors and latent factors, based on aircraft accident cases.

2.3. Theoretical Background

This section briefly covers the principles and mathematical theories upon which probabilistic graphical models are founded. Bayesian networks have become a major discipline of study in the larger artificial intelligence domain and it is beyond the scope of this research to cover the wide arrays of causal models and their exact and approximate learning algorithms that have been discovered over the years.

2.3.1. Basics of Probabilistic Models

Bayesian networks are composed of two primary components—data structure and conditional probability distribution. The structural representation of a Bayesian network is a Directed Acyclic Graph (DAG). It is a data structure for representing the joint probability distribution of a set of variables by incorporating a set of conditional independencies. The link between any pair of variables represents the correlation or dependency between them. The second major component of a Bayesian network is the set of local probabilities, Conditional Probability Distribution (CPD), which represents the dependencies of each variable in the network given their parents.



Marginal Probability of RI

P(RI) = (.65*.11*.25) +

(.45*.11*.75) +

(.4*.88*.25) +

(.1*.88*.75) =

.209

Figure 11: DAG & CPD of Simple Bayesian Network for Runway Incursion

The encoding of the dependency and independency constraints are realized by applying probability calculus. For each variable in the model there is a corresponding conditional probability distribution given each possible joint assignment of values to its parents. Variables without parents are conditioned on empty set of parents which renders unconditional probability distribution (marginal distribution). The formal definition of a Bayesian network for variables $\boldsymbol{X}$ is a pair of (G, Ɵ), where

- G is a directed acyclic graph over $\boldsymbol{X}$ (structure) and
- Ɵ is the set of CPDs, one for each variable in $\boldsymbol{X}$ (parameters)

2.3.2. Random Variables and Probability Calculus

In DAG, the nodes represent random variables which can be discrete such as severity = (Minor, Major, Hazardous) or continuous such as wind speed. In the majority of cases Bayesian networks are used to model probability distribution on discrete random variables. Even when they are used to model continues variables, they are usually applied by discretization, for instance, wind speed can be grouped into ranges such as 0-5, 6-10, 11-15 knots etc. The nodes can also represent functional variables which are defined as a function of their parent variables.

There are two contending interpretations in practical application of probability; "Frequentist probability" and "Bayesian probability". In the frequentist (objectivist) interpretation, probability is a random process which denotes a relative frequency of the outcome of an experiment while Bayesian (subjectivist) assigns a degree of belief to an outcome as a probability. For learning the parameters in this dissertation I will use the frequentist approach mainly because the analysis is largely a data-driven one, no elicitation of opinion from domain experts will be incorporated for the purpose of determining probabilities of random variables. Formal theory of probability definitions satisfies the following properties.

For discrete probability distributions,

$$f(x)\ \varepsilon\ [0,1]\ for\ all\ x\ \ \varepsilon\ \Omega$$

$$\textstyle\sum_{x \varepsilon \Omega} f(x) = 1$$ Where,

- *Ω is the sample space and*

- *f(x) is a probability mass function mapping a point in the sample space to a probability value*

For continuous probability distributions,

$$f(x) \geq 0$$

$$\int_{-\infty}^{+\infty} f(x)dx = 1$$

$$F(x) = P(X \leq x) = \textstyle\int_{-\infty}^{x} f(x)dx$$ Where,

- *f(x) is probability density function and*
- *F(x) is cumulative distribution function*

2.3.3. Parameterization of Independent Variables in DAG

The primary objective of Bayesian networks is to represent the joint distribution P over a set of random variables

$$\chi = \{X_1, X_2, \dots, X_n\}$$

With large number of variables, computing the joint probabilities can become expensive. It also gets increasingly difficult to elicit experts' opinion for Bayesian networks as the number of variables increases. For n independent variables $X_1, \dots, X_n$, the joint distribution is given by,

$$P(x_1, x_2, \dots, x_n) = P(x_1)P(x_2) \dots, P(x_n)$$

$$= \prod_{i} P_i$$

Without any independence assumption, this representation requires 2^n possible values (parameters) and $2^n - 1$ number of probabilities for binary variables. The size of the parameters in the joint distribution is exponential in the number of variables of interest; for k states and n variables it takes $O(k^n)$. Similarly, computing a marginal such as $P(x_1)$ requires summing over (k^{n-1}) states. For instance, in ATSAP dataset there are more than 300 binominal causal variables hence, the number of parameters in the joint distribution will become prohibitively large number to represent jointly without a compact model.

2.3.4. Parameterization of Conditional Variables

Bayesian networks use a data structure in the form of directed acyclic graph to provide a general purpose modeling language to represent a set of random variables compactly. Applying Markov property, there are no direct dependencies in the model except those explicitly connected by arcs, this is called Independence-maps, or I-maps. Hence, a compact representation of a joint distribution is achieved by using conditional probabilities on only the variables that depict dependencies. As the number of variables increases, assumptions of Markov independence property will significantly reduce the number of probability computations required to solve the joint distribution. For every variable X in the DAG G and its parents Π, there needs to exist a probability $P(x|\pi)$ for every value x of variable X and every instantiation π of parents Π.

From chain rule of probability,

$$P(x_1, x_2, \dots, x_n) = P(x_1)P(x_2|x_1) \dots, P(x_n|x_1, \dots, x_{n-1})$$

$$= \prod_i P(x_i | x_1, \dots, x_{i-1})$$

$$= \prod_i P(x_i | \Pi(x_i))$$

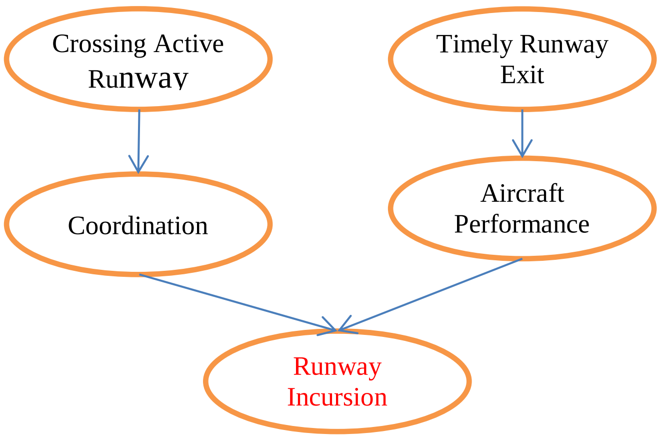


Figure 12: Local Independence Logic of a DAG

In the simple runway incursion DAG shown in figure-12, for instance, having no knowledge about the coordination issues for a particular incident, crossing active runway is relevant for computing the probability of runway incursion. However, if we become aware about the fact that coordination issues were not involved in causing the event, crossing active runway incursion becomes irrelevant, that is, crossing active runway is independent of runway incursion given coordination. Similarly, if aircraft performance is known to be not a causal or contributing factor, no additional information will be gained from timely runway exit as to why the runway incursion event occurred. Hence, using first letter abbreviations for each variable for the DAG in the above example we only need the following conditional properties.

$$P(CAR), P(TRE), P(C|CAR), P(AP|TRE), P(R|C, AP)$$

Markov properties are based on conditional independencies. For V variables, parents of V $\Pi(V)$, and non-descendants of V $\Psi(V)$ in a DAG, the compact representation is formulated by the following independence statement and it is called local independencies.

$$V \perp \Psi(V) | \, \Pi(V) \text{ , } \textit{for all variables V in DAG G}$$

That is, every variable in the DAG is conditionally independent of its non-descendants given its parents, and it's referred to as *Markovian Independencies*. Bayesian networks explicitly express conditional independencies in probability distributions by applying Markov property. Hence, understanding the conditional independence relations of variables in the model is critical to build Bayesian networks.

2.3.5. Conditional Independence Test

In the simple case of singly connected DAG there are four possible data structures with three distinct types of connections; two chained ones, causal-to-effect and a common cause, and one common effect. Consider the following three variables, incorrect frequency, loss of communication, and incident in a DAG G in figure-13 and 14 below.

2.3.5.1. Cause-to-Effect (Chain)

In the absence of evidence about loss of communication, if we learn that there was incorrect frequency usage, it increases the likelihood of loss of communication which in turn increases the chance of incident happening. However, if we already know that loss of communication has occurred, we don't get any additional information from the fact that whether or not there was incorrect frequency usage. Therefore, when there is no evidence, a serial connection is active and hence the variables involved in the chain are dependent, and it is inactive upon the presence of evidence on a variable in the chain which makes the variables independent. Merely reversing the causal link in serial connection does not change the information flow and the dependencies between the variables, hence, the two chains in figure-13 are equivalent.

$$Incident \perp Incorrect\ Frequency \mid Loss\ of\ Communication$$

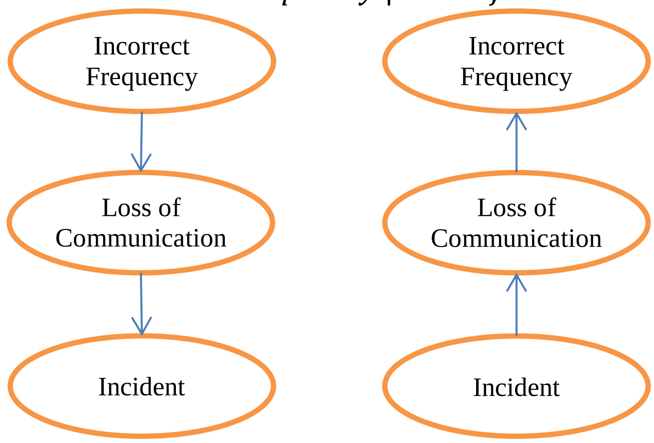


Figure 13: Causal-to-effect DAGs

2.3.5.2. Common Cause (Divergent)

In the absence of any information about adverse condition (refer common cause DAG in figure-14), if we learn that there was communication problem, the probability of the existence of an adverse condition increases, and as the probability of adverse condition increases it becomes more likely that there was coordination problem as well. However, if we have been already informed about the presence of an adverse condition, we won't gain any additional information about coordination from communication or vice versa. Therefore, information flow in common cause connections behaves similarly to serial connections. Absence of evidence in the cause makes the effects dependent and they become independent when we learn about the common cause.

$$Communication \perp Coordination \mid Adverse\ Condition$$

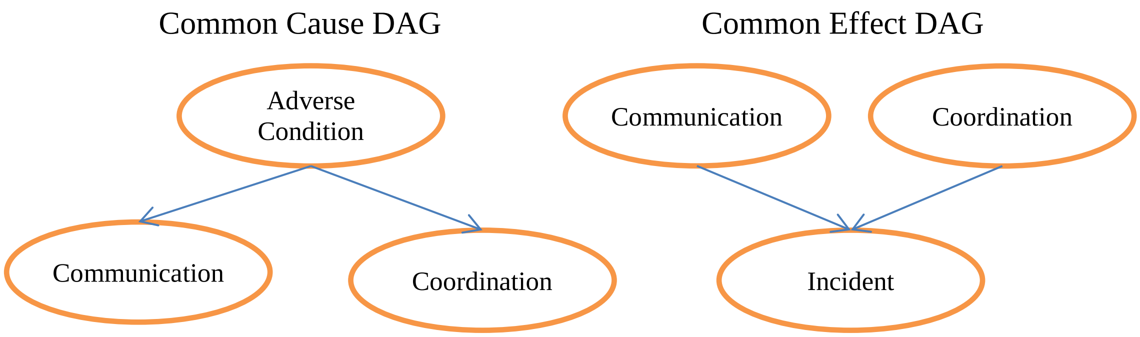


Figure 14: Common Cause and Effect

2.3.5.3. Common Effect (Convergent)

When there is no evidence on incident (common effect in figure-14), the two causes, communication and coordination are independent, no active connection for information to flow from one to the other. As we learn that incident occurred, the connection between the two causes opens for information to flow making them dependent. In the presence of incident, if we also learn that there was no communication problem, the likelihood of coordination increases implying that the incident was caused by coordination issues. In other words, in common effect, the parents are marginally independent, but conditionally dependent. Hence, information flow and variable dependencies are different in common effect connection as opposed to the serial and common cause connections.

$$Communication \not\perp Coordination \mid Incident$$

For longer trails of variables $\chi = \{x_1, \ldots, x_n\}$, the logic for the active connection remain the same. For the whole connection in the trail to be active, information needs to flow through every node in the trail.

In all the configurations described above, the dependence or independence property of the connections are described through the flow or blockage of information through the links. When the links are active, information flows through them and the variables that are connected by the links are dependent. On the other hand when the links are inactive, information doesn't flow though the links and the variables that are connected by such links are independent. A common term that is used to describe active connections in Bayesian networks is d-connection while d-separation is used for those connections that are inactive, the d in d-separation/connection stands for dependence. Given a set of variables **X, Y, Z** in DAG G, **X** and **Y** are said to be d-separated given **Z** if there is no active trail between any node X in **X** and Y in **Y** given **Z**.

$$I(G) = \{X \perp Y \mid Z) : d - sep(X, Y|Z)\}$$

2.3.6. I-Equivalence

The DAG G can be abstracted using the set of conditional independencies, i.e. a DAG is composed of independence properties. Such abstractions allow for different DAG structures to be equivalent based on the set of independencies they represent. For instance, the cause-to-effect structure and the common cause in section 2.3.5 abstract the same set of conditional independencies. As a result, DAGs of different structures may encode the same independencies and such graphs are said to be I-Equivalent.

2.3.7. Learning Bayesian Networks

Bayesian networks that model real world problems usually involve a fairly large number of variables and as a result without applying some level of automation it can be very difficult to construct such models. In fact one of the main challenges to model problems using Bayesian networks is the difficulty of eliciting knowledge from experts to determine the structure and probability distributions of the network unique to the domain. For years researchers have been working on algorithms to learn Bayesian networks from data to assist the knowledge gathered from experts. In cases where it is difficult to elicit knowledge from domain experts, data alone may be used for building reasoning models. Primarily, learning Bayesian networks involve two components; the causal structure of the network, the DAG, to discover the dependencies in the model, and learning the parameters of the structure, the CPDs. There are various types of algorithms to do both but it is beyond the scope of this research to cover them in detail. Once the DAG and CPD of the networks are learned, the model can be used for purposes of classification, diagnosis/causation, or prediction. Like many other machine learning algorithms, learning Bayesian networks from data can be done from samples; a training set is used to train the model and testing set is used for validating the learned model.

2.3.7.1. Parameter Learning (Estimation)

After the structure (DAG) has been created, either by eliciting knowledge from experts or using algorithms from data, a Bayesian network needs to be parameterized. Parameterization involves specifying conditional probability distributions on each variable in the network, which also can be done either through assistance from domain experts or learning from data or a combination of the two. The two main approaches of parameter learning from data are maximum likelihood estimation and Bayesian parameter estimation. Below is a brief discussion of both approaches for complete data; the learning algorithms for incomplete data are more involved—Expectation Maximization and Gradient Descent are few of the popular algorithms for learning from data with missing values.

2.3.7.2. Parameter Learning using ML Estimation

Maximum likelihood estimation (MLE) is based on the likelihood principle which favors estimators that maximize the probability of observing the dataset, which is assumed to be independent and identically distributed (IID). Assume a binomial model of a single variable, for instance, Aircraft Performance in one of this project's networks, which can take the binary states Factor (T) and Not-Factor (F). Also assume that the probability of the Aircraft Performance being a Factor to an incident is controlled by a constant but unknown parameter $\theta \in [0,1]$, therefore, the probability that it is Not-Factor is $1-\theta$.

Now if we have a sample of cases of 5 incident reports in which 2 of the incidents were caused by Aircraft Performance, then the probability of this set of sequences is

$$P(T,T,F,F,F:\theta) = \theta\theta(1-\theta)(1-\theta)(1-\theta) = \theta^2(1-\theta)^3$$

The probability depends on the value of θ hence it is a function of θ. Therefore, the likelihood function is

$$L(\theta:T,T,F,F,F) = P(T,T,F,F,F:\theta) = \theta^2(1-\theta)^3$$

For a binary variable if we have C1 number of cases from state 1 and C2 cases from state 2 of a dataset *D*, the likelihood function is

$$L(\theta : D) = \theta^{C1}(1-\theta)^{C2}$$

It is easier to work with the log-likelihood since the products are replaced with summations and the two functions are monotonically related.

$$l(\theta : D) = C1 \log(\theta) + C2 \log(1-\theta)$$

Solving for θ and denoting by $\hat{\theta}$ for estimate, by differentiating the log-likelihood and setting the derivative to 0,

$$\hat{\theta} = \frac{C1}{C1 + C2}$$

In our example above, the probability of Aircraft Performance being a factor is

$$P(F) = \hat{\theta} = \frac{2}{2+3} = 0.4$$

In general the likelihood function of a network DAG G and the set of all parameter estimates θ for G and $P_\theta(.)$ be the probability distribution induced by structure G and estimates θ,

$$L(\theta : D) = \prod_{i=1}^{N} P_\theta(d_i)$$

And the ML estimator is

$$\hat{\theta} = argmax_\theta \, L(\theta : D)$$

2.3.7.3. Parameter Learning using Bayesian Estimation

Bayesian estimator is based on conditioning a prior distribution P on parameter $\theta \in [0,1]$ and using the given dataset as evidence to compute the posterior distribution to estimate the parameter; note that θ is treated as a random variable in this setting. For the binomial model we considered above for the MLE, the joint distribution of the dataset and θ is,

$$P(T,T,F,F,F,\theta) = P(T,T,F,F,F\,|\theta)P(\theta)$$

$$= \theta^2(1-\theta)^3\mathrm{P}(\theta)$$

In general for n incidents with evidence e of only m of them caused by Aircraft Performance,

$$\mathrm{P}(\theta|\mathrm{e}) = \theta^m(1-\theta)^{n-m}\mathrm{P}(\theta)$$

This is a product of the likelihood and the prior distribution. The posterior distribution is,

$$\mathrm{P}(\theta|\mathrm{T,T,F,F,F}) = \gamma\mathrm{P}(\mathrm{T,T,F,F,F}|\theta)\mathrm{P}(\theta)$$

$$\text{Where } \gamma = 1/\mathrm{P}(\mathrm{T,T,F,F,F})$$

The posterior is proportional to the product of the likelihood and the prior, and the denominator is a normalizing factor to make the posterior a proper density function. The above equation needs a prior distribution over θ although the specific type of the distribution is less relevant. However, one of the commonly used families of distributions for prior belief is beta distribution. A beta distribution is parameterized by two hyperparameters α_1, α_2 both of which are positive reals.

$$\theta \sim Beta(\,\alpha_1,\,\alpha_2)$$

$$P(\theta|\,\alpha_1,\,\alpha_2) = \gamma\theta^{\,\alpha_1-1}(1-\theta)^{\,\alpha_2-1}$$

$$where\,\gamma = \frac{\Gamma(\,\alpha_1,\,\alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)}\,, and\;\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt,\;Gamma\;function$$

In our binomial example α_1 may represent Aircraft Performance being a factor to an incident and α_2 not a factor.

The expected value of the beta distribution is,

$$E(Beta(\alpha_1, \alpha_2)) = \int \theta P(\theta | \alpha_1, \alpha_2) d\theta = \frac{\alpha_1}{\alpha_1 + \alpha_2}$$

In our example of m Aircraft Performance factors in n incidents,

$$P(\theta | \alpha_1, \alpha_2) = \gamma \theta^{\alpha_1 - 1 + m} (1 - \theta)^{\alpha_2 - 1 + (n - m)}$$

This is another beta distribution with different parameter values,

$$Beta(\alpha_1 + m, \alpha_2 + n - m)$$

Therefore, both the prior and the posterior are in the same family of beta distribution and such distributions are known as conjugate family of distribution. The convenience of conjugacy is one of the reasons for using beta distribution as a prior in Bayesian parameter estimation.

If we assign a $Beta(3,3)$ prior in our example (figure-15), and with the observation of 2 Aircraft Performance factors in 5 observations,

$$P(\theta|3,3) = Beta(3 + 2, 3 + (5 - 2) = Beta(5, 6)$$

The expectation, $E = \frac{5}{5+6} = 0.45$

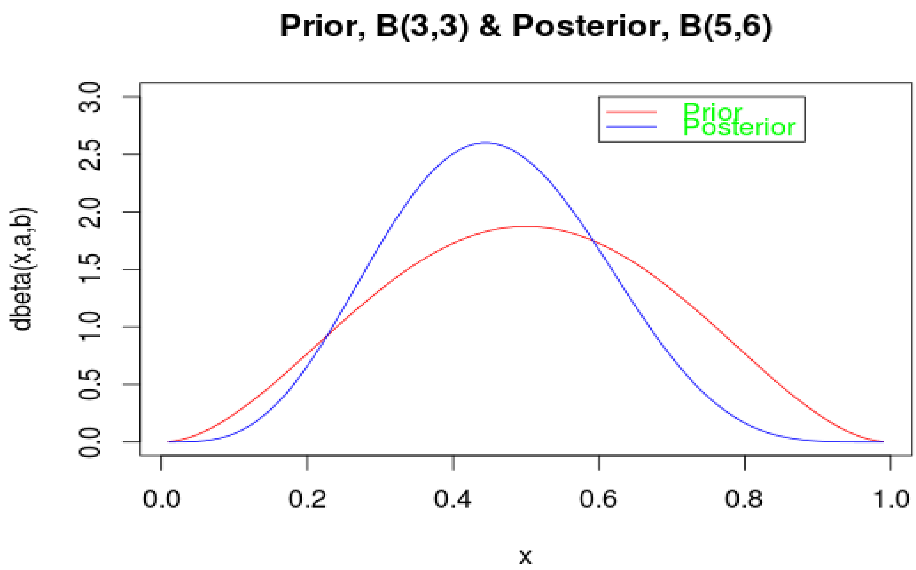


Figure 15: Prior and Posterior Plots

For multinomial variables we may use the Dirichlet prior distribution which is a generalization of beta distribution for variables with more than two states. For a variable with k states,

$$\theta \sim Dirichlet(\, \alpha_1, \dots, \alpha_k)$$

Probability of the ith state, $P(X_i) = \frac{\alpha_i}{\sum_{j=1}^{k} \alpha_j}$

For k independent states, $P(\boldsymbol{\theta}) = \prod_{i=1}^{k} P(\theta_i)$

Therefore, upon observing the ith state, the posterior distribution becomes,

$$Dirichlet(\, \alpha_1, \dots\ \alpha_i + 1, \dots, \alpha_k)$$

We can apply the same approach on all the variables in the network by iterating through each variable to parameterize the full network.

2.3.7.4. Structure Learning

In the network parameterization discussion above, the assumption we made is that the structure is given. However, in any real world problem the structure of the network needs to be learned from data or elicited from domain experts. It is important to remember that due to potential I-equivalence among various network structures for the same domain, the DAG may not be unique. In general, learning network structure is much harder than learning network parameters; it is $NP - hard$ problem, and as a result sometimes heuristic methods are used along with algorithm-driven learning.

Primarily there are two approaches for learning Bayesian structure; constraint-based learning and score-based learning. In addition, model averaging methods which generate an ensemble of possible structures can be considered as a third approach. Constraint-based learning is based on discovering independencies between variables in the data and model the structure to reflect these independencies. Score-based methods on the other hand are used by scoring all the potential structures in the domain and selecting the model with the highest score. Similar to parameter learning, score-based structure learning may be learnt by likelihood principle or Bayesian approach.

For the models learnt in this dissertation part of the structure is built based on the information embedded in the dataset, that is, we know the causal factors are correlated to the target events, hence we link them in the network. Also, since the hierarchical abstraction is only for the purpose of simplifying the network structure, there is always a link between the parent and its children in the hierarchy. However, the relationships between causal factors are unknown, which requires "partial" structure learning. I use Tree-Augmented Naïve (TAN) structure learning to discover associations between any pair of causal factors given the structure learned using the top causal factors identified for each event. The methodologies chapter provides the description about TAN structure learning and the justification for applying it in this setting.

2.3.7.5. Likelihood Scoring

The objective in likelihood scoring is to maximize the likelihood function, i.e. to find a structure that makes the observed data as probable as possible. For k possible structures $G = \{g_1, \dots, g_k\}$, the likelihood score (LS) for the i^{th} G is given by,

$$LS(g_i : \mathcal{D}) = l(\hat{\theta} : \mathcal{D})$$

Where $l(\hat{\theta} : \mathcal{D})$ is the log-likelihood function as defined above in the parameter learning section and $\hat{\theta}$ is the maximum likelihood parameter for g_i.

ML ignores a conditional independence unless it holds exactly in the empirical distribution, which is unlikely in most samples, and hence it tends to create fully connected networks which causes over fitting by mirroring the training dataset.

2.3.7.6. Bayesian Scoring

Similar to Bayesian parameter learning, we place a prior distribution over the structure about which we have uncertainty and its parameters. For k possible structures $G = \{g_1, \dots, g_k\}$, the posterior probability of the i^{th} G is given by,

$$P(g_i|\mathcal{D}) = \frac{P(\mathcal{D}|g_i)P(g_i)}{P(\mathcal{D})}, where\ P(g_i)\ is\ the\ prior$$

The $P(D)$ is a normalizing factor which doesn't contribute in differentiating structures and the prior $P(g_i)$ is irrelevant compared to the marginal distribution $(D|g_i)$. Therefore, the Bayesian Score (BS) in log form to avoid numeric underflow for large networks is given by,

$$BS(g) = logP(\mathcal{D}|g)$$

$$Marginal\ likelihood, P(\mathcal{D}|g) = \int_{\Theta_g} P(\mathcal{D}|\theta_g, g)P(\theta_g|g)d\theta_g$$

Where $P(\mathcal{D}|\theta_g, g)$ *is the likelihood of the observed data given the network and* $P(\theta_g|g)$ *is the prior distribution*

Unlike the maximum likelihood score which uses the maximum of the function, the marginal likelihood score uses the average of the function based on the prior distribution.

2.3.8. Inference and Reasoning

Inference, also called probability propagation, belief updating or prediction, in Bayesian networks involves determining the likelihood of some variables taking certain states upon learning the states of one or more variables in the model. It is the computation of posterior probability distribution for a set of query nodes upon getting evidence on a subset of the network nodes. In the following simple model, if we have evidence that Timely Speed Adjustment is a causal factor of the Aircraft Performance, the probability that it is also caused by Compression on Final is higher, see figure-16 below.

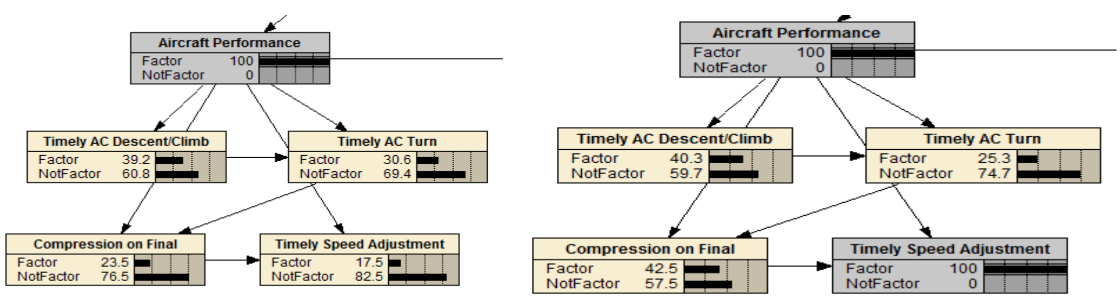


Figure 16: Evidence of Timely Speed Adjustment

Bayesian inference is primarily based on Bayesian philosophy, which lies in the interpretation of Bayes' theorem to propagate flow of information through the network.

$$P(x|e) = \frac{P(e|x)P(x)}{P(e)}$$

This is a simple theorem of probability that can easily be proved using definition of conditional probability. It implies that the probability of event x conditioned upon evidence e is the product of the likelihood $P(e|x)$ and the probability of x before any evidence $P(x)$, which is called the prior, normalized by $P(e)$ so that the total conditional probabilities sum to 1. It is basically adjusting of one's belief given new evidence, and it is usually known as posterior probability. The evidence can come as hard evidence, with 100% certainty in the given state, or soft/likelihood evidence with probability of less than 100%.

There are two major inference algorithms—exact and approximate, and the type of the network and the complexity of the model dictate the kind of inference algorithm applied to the problem. Iterated application of Bayes' theorem may well suffice for a simply chained network, while networks with multiple paths to nodes may require more sophisticated algorithms. Similarly, exact inference algorithms may be available for simpler networks, but such algorithms may involve expensive computations in which case approximate algorithms can give sufficiently satisfactory solutions. In this research I use Netica's software Application Programming Interface (API), which uses junction tree algorithm to propagate evidences by message passing. A message passing algorithm (Pearl, 1988) is an efficient inference algorithm which exploits local independencies to pass information between neighbors recursively.

2.3.9. Decision Network

Standard Bayesian networks don't provide any specific recommendations to alter, minimize, or optimize the interrelationships among the causal and effect variables in the model. Moreover, classical probabilistic queries don't depend on the causality of the network so long as they encode the correct distribution and hence it is not always predictable how intervening influences the causality in the network. However, intervening or taking actions on causal models can lead to a different outcome of the distribution in the network thereby influencing the natural course of events. By assigning a value or utility to different situations, we can rank each possible outcome and influence the result according to the rank assigned.

In this research I will incorporate a simple cost-based utility function in the runway incursion event causal model to demonstrate the value of converting ordinary probabilistic model to a decision network. Such a model suggests specific actions to be taken in order to maximize the utility, which is to minimize the occurrence of causal factors according to their frequency in causing incidents and their severity. For instance, by addressing the causal factors that lead to major incidents, we can lessen the effects of the problems in causing potential accidents. Utility functions that are involved in most models incorporate monetary values as taking any action usually incurs cost. However, due to the scope of this research, I will limit the financial aspect of the cost associated with taking a particular action such as fixing any specific problem in this domain.

In figure 17, the control variables are the actions that need to be taken in order to reduce the likelihood of the causal factors that eventually lead to the underlying event. In real world problems the actions we take are not usually perfect, they don't entirely remove the problems, they only reduce them. As a result, depending on the nature of the event we are trying to address, we may place mitigation variables that enable us reduce the consequence of the event if it occurs. In decision analysis, we measure the resources required to place such control and mitigation variables against their utility and the reduction of the probability of the undesired event. Decision analysis and the utility quantification process are covered in detail in the methodologies chapter.

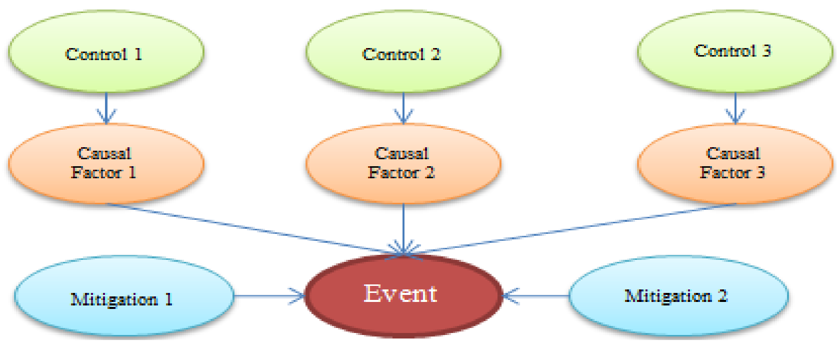


Figure 17: Decision Network with Control & Mitigation Variables

3. METHODOLOGY

3.1. Categories of Hierarchical Structures

In most complex systems such as the NAS which have a large number of interacting cause and effect variables, the complexity is usually abstracted using hierarchies and categories. For instance, the two primary areas of causal factors for various undesired events in ATC operation are Individual and Weather. There may be different ways of structuring the taxonomies of such categories, but any type of abstraction will most likely involve some level of hierarchical structure. Figure-18 shows the three level hierarchies of the two categories as used in the ATSAP program.

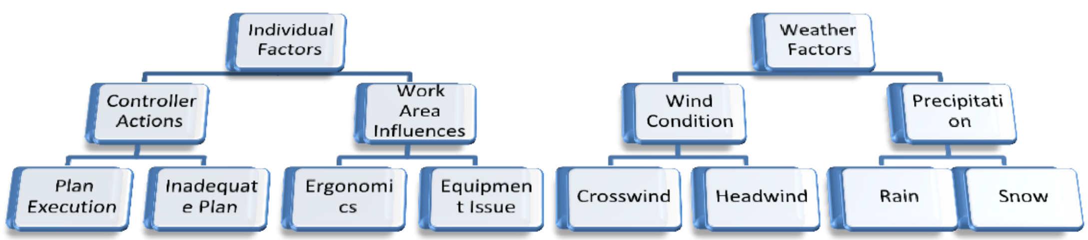


Figure 18: Hierarchies of Individual & Weather Causal Factors

In hierarchical structures, the variables at the higher levels serve as "composite" variables and are primarily used to categorize the lower level details. The variables at the very bottom of the hierarchy, on the other hand, are observable, and hence the quantification of the higher level categories is done from these observations.

To model causal interactions, graphical models use directed links to represent the causality between parent and child variables. In probabilistic causal models, an arc directed from node X to node Y is used to model the causal effect of variable X on variable Y. The central theme of a probabilistic model is such that a variable is conditionally independent of its non-descendants given all its parents, and when such a model is a causal one, the parents are the causal variables. However, standard probabilistic causal models have limitations for modeling hierarchical structures. In a typical hierarchical causal structure a set of variables at the higher level act as causes to a set of effects on the next level and those in turn become a set of causes for the next lower level variables creating hierarchical chains of cause and effect connections.

3.2. Modeling Hierarchies through Categorical Variables

In classical probabilistic causal models, a set of random variables are connected through directed edges based on the dependencies among the variables and hence, complex causal structures are usually represented using flattened models where by each causal variable is connected to the effect variable. Building such networks and doing inferences on them are relatively easier when small numbers of variables are involved in the network. However, in models with large number of causal variables connected to the same effect, it is difficult to compute the conditional probabilities as there is exponential number of conditional probabilities for all possible combinations of states of the causal variables. Also, as the number of parent nodes for a variable increases the parameter estimation becomes less reliable due to the data fragmentation caused by all the possible combination of the parents' states. In the structure with prepositional causal variables (shown in figure-19), a flattened model is used to directly connect all causal variables to one effect variable.

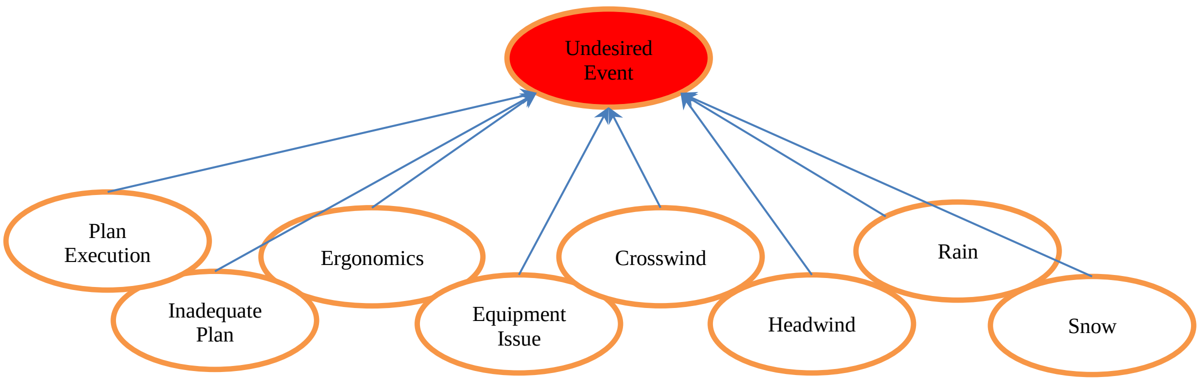


Figure 19: Flattened Causal Model Structure

In this flattened model there are 8 causal parents to the same effect and hence the conditional probability of the effect node has 2^8 parameters. With large number of variables the number of parameters increases exponentially. One approach to reduce the number of parameters is to introduce layers of categorical variables in which the variables at one layer acting as causal factors to the variables at the next layer. In the following categorical model (figure-19), the eight causal variables are broken into three layers; the variables at the intermediate layers represent all the causal variables in the flattened model.

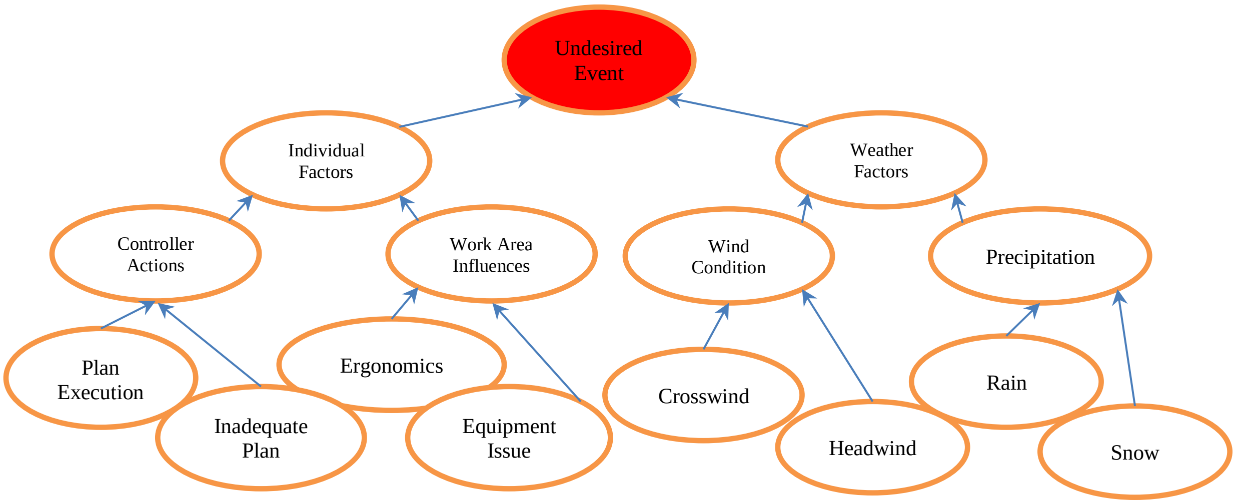


Figure 20: Layered Categorical Model Structure

In the categorical model, computing conditional probabilities at each layer involves a smaller number of variables there by reducing the computational complexity and avoiding the data fragmentation caused by large number of parents. Also, it is a lot easier for humans to understand the causal effect of any particular set of variables on a given effect by providing encapsulation at each layer. For instance, unless one is interested in the root causes of the undesired event, the above model allows abstraction of the analysis of the event concentrating on just two causes, weather and individual factors.

The side effect of the hierarchical simplification is that any parent-child relationship within a hierarchy becomes partially deterministic. For instance, if we learned that Crosswind is involved in the incident, we also know that it is Weather related event, hence deterministic relationship exists, but knowing that it is a weather-related incident doesn't necessarily mean Crosswind is the lower level causal factor, hence probabilistic relationship exists. On the other hand, the partially deterministic behavior can be beneficial to further simplify the reasoning process upon learning evidences. For instance, in the hierarchical model above, if we learned that weather problem was not involved in causing or contributing to the undesired event in any way, we can provide negative evidence on the Weather variable alone and effectively remove all the nodes that are sub categories of the Weather hierarchy making the inference a lot simpler.

In ATSAP ATC taxonomy, there are more than 300 causal factors contributing to 21 undesired event types. The event classification has three high level categories and each category contains the specific undesired event.

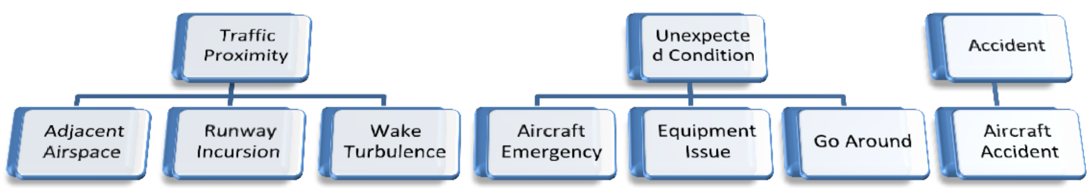


Figure 21: Hierarchies of Undesired Event Types in ATSAP

Similarly, there are 15 high level categories of causal factors with sub categories ranging from two to four levels. By directly representing the hierarchical structure of the domain using categorical variables, a level of simplification is achieved in the probabilistic causal model. The following structure is the output of an automation program and represents the full hierarchical structure of the events and causal factors. All the connections are done from one hierarchy to the next which significantly reduces the total number of links among variables.

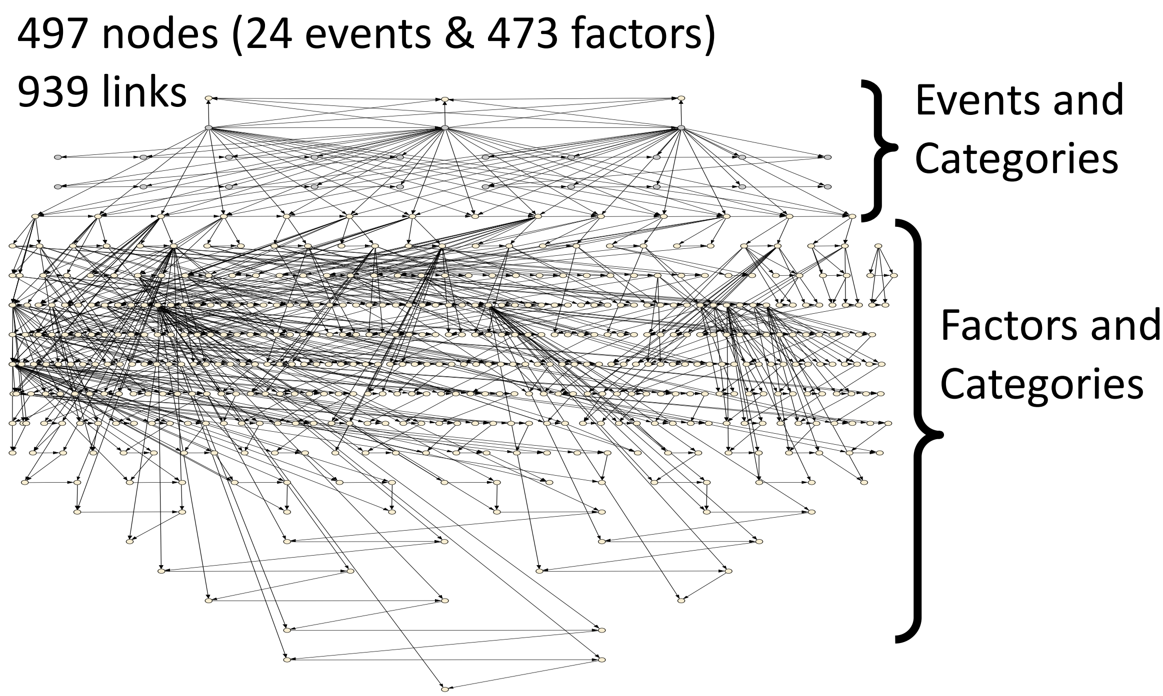


Figure 22: Fully-Represented Categorical Probabilistic Causal Model

3.3. Identification of Top Causal Factors of Events

When the structure represents domains with large number of causal and effect variables, in the order of hundreds or even thousands, the simplification realized through the use of categories and subcategories won't be quite sufficient for humans to interact with the model and make inference. In addition, it is unlikely that analysts and decision makers will treat all the causal factors equally regardless of their impact on the undesired event. Therefore, identification of a smaller number of top causal factors for each event is a vital component to further simplify the modeling process. For instance, the model in figure-23 shows Runway Incursion event along with six top causal factors based on

ATSAP historical data. The red circular node is the target event variable, the green node is the high level category of the event, the nodes shown in orange are the lowest level cuasal factors in the hierarchy, and the dark blue nodes are the higher level categories of the respective factors.

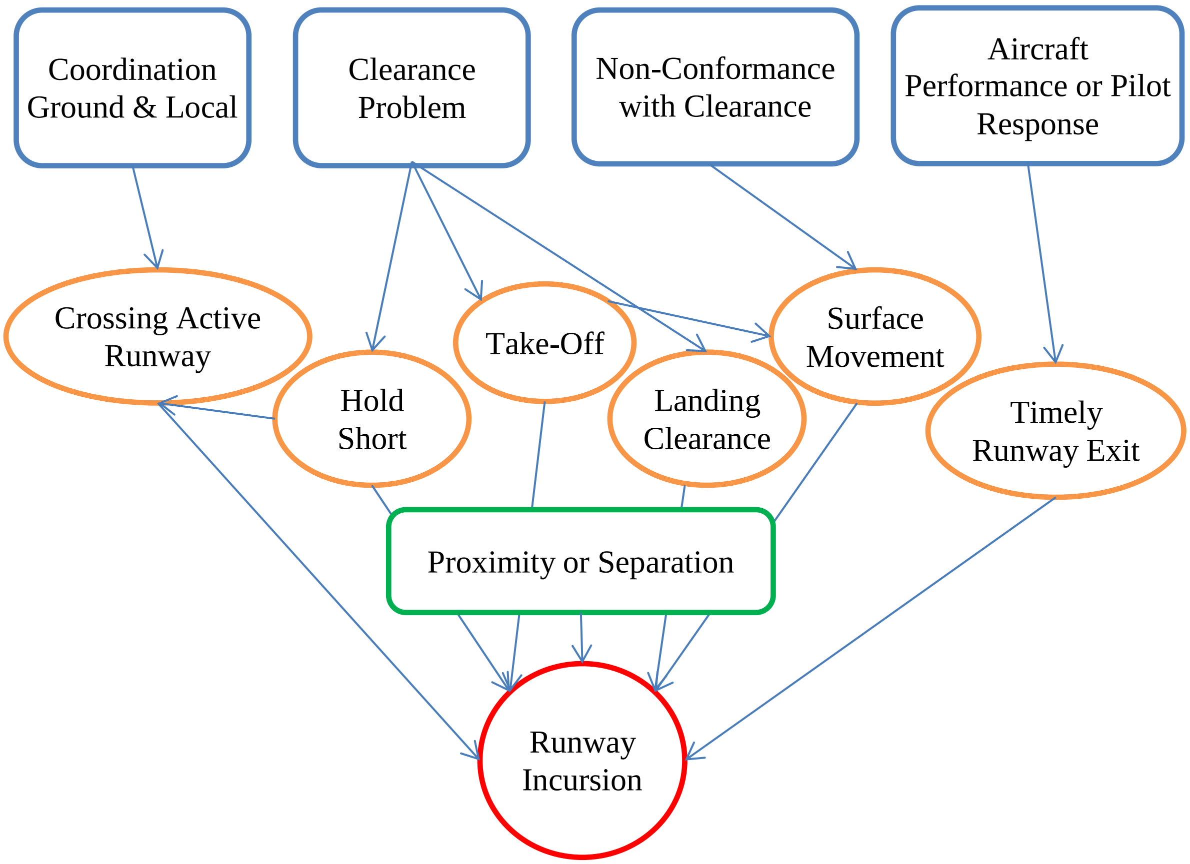


Figure 23: Runway Incursion Event with Six Top Causal Factors

Reducing the number of causal factors to only a small number of highly correlated causal factors is an attribute selection problem. In probabilistic causal models, a known approach of selecting attributes are done during the structure learning process from data, in which variables that are not relevant are excluded. In this research I introduce an attribute selection approach based on sensitivity analysis and performance measure of the probabilistic model.

3.3.1. Sensitivity Analysis of Bayesian Networks

Sensitivity analysis is primarily used to test the robustness of a probabilistic model. It is a mechanism to measure the impact of one or more variables on a target variable in probabilistic graphical models. Sensitivity analysis is primarily used to check the validity of probabilistic models that are built through the solicitation of expert opinions. It serves as a tool to correct local probabilistic distributions when the impact of a set of variables on the target variable is out of expected ranges, excessively high or low that cannot be explained within the context of the given model. It can also be used to measure changes on the query variables in order to enforce certain constraints, such as a pre-specified level or bounds of posterior output on the target variable.

For instance, if one builds a probabilistic model for runway incursion along with its top causal factors with the help of expert judgment, sensitivity analysis can be performed to measure the change of the probability that occurs on the runway incursion event when we provide evidence on some of the causal factors. If the change is deemed excessive by the expert, then local probability distributions of the affected causal factors may need to be modified to correct the discrepancy. On the other hand, if the parameter changes on the causal factors are found to be inadequate, then the network structure may need to change through the addition or removal of some causal factor nodes.

3.3.2. Factor Selection using Performance Measure

The identification of top significant causal factors for a given event is a type of feature selection problem. With a large number of causal factors the accuracy of classifying events may increase at the expense of complexity. However, it may be preferable to only include a smaller number of causal factors with an acceptable level of accuracy thereby reducing the complexity of the model.

In this research I introduce a selection criterion that follows a two-step process. In the first step, the impact of each causal factor is measured using a posterior calculation and the relevant causal factors are ranked as described in the impact of factors section below. In the second step, multiple networks are created iteratively by incorporating causal factors according to their rank. The steps of the model simplification process are,

1. The impact of each causal factor for the target event is calculated as the difference of prior and posterior probabilities for ranking
2. A network with the given event as a target and a causal factor with the highest rank is created
3. The network parameters are learned using the training dataset
4. The performance of the network is measured using the test dataset and the classification accuracy is calculated using Brier score (section 3.3.4)

The process continues, and more high-rank causal factors are added, the network retrained, and the reduction of the Brier score of subsequent iterations is calculated. The stopping criteria for not adding more causal factors is such that the reduction of the Brier score on the test dataset is smaller than the immediate previous iteration. The final network is comprised of the top causal factors linked to the target event variable along with their conditional relative frequency values. At this stage, any potential correlation that exists between any pair of causal factors is not discovered; the partial structure learning section describes that process.

The algorithm for top causal factors identification process is,

1. Relevant Causal Factors: CFs = {} // initialize empty set of relevant causal factors
for each causal factors in the data set
2. $P_i \leftarrow P(C_i|E) - P(C_i)$
3. $if\ P_i > 0$
4. *CFs +=* C_i
5. Rank relevant causal factors: CFs //Sort in decreasing order of P_i
6. Brier score: BS = 1
7. Brier score reduction BSR = 0
8. Top_CFs = {} // initialize empty set of top causal factors
9. for each CF in CFs
10. Top_CFs += CF
11. Create network from Top_CFs and target event E
12. Estimate parameters using training set
13. Calculate current Brier score BS_Cur using test set
14. BSR_Cur = BS – BS_Cur
15. If (BSR_Cur <= BSR)
16. Remove CF from network
17. Break //Stop iterating
18. BS = BS_Cur
19. BSR = BSR_Cur

Figure 24: Algorithm for Top Causal Factors Identification

3.3.3. Posterior Probability to Measure Impact of Factors

In the first phase of the top causal identification algorithm, the impact of each causal factor on a given event is measured using a posterior-based sensitivity analysis. One common approach to do sensitivity analysis is to vary the parameters of a variable by holding the other variables fixed and measure the changes on the target variable. The second approach is to compute the partial derivative of the target variable with respect to each of the parameters in the network (Laskey, 1995). In this research I use a simple naïve Bayes-like intermediate network to measure the impact of the target variable on each of the causal factors. In this approach, similar to naïve Bayes, all the causal factors are independent given the evidence on the target event. Therefore, a simple posterior calculation provides the measure of the impact of each causal factor only from the given event without the effect from other causal factors.

$$P(C_1, \ldots, C_n|E) = P(C_1|E) \ldots P(C_n|E)$$

$$P_i \leftarrow P(C_i|E) - P(C_i) \quad \text{// Impact (change of probability assignment)}$$

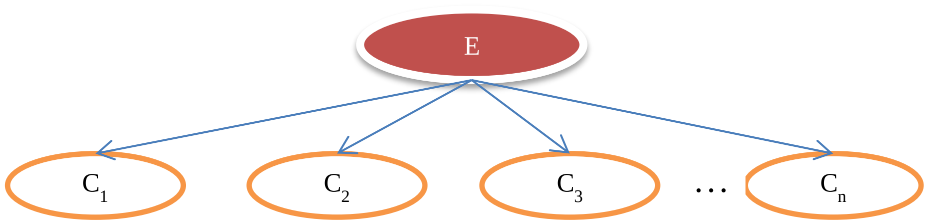


Figure 25: Intermediate Network to Measure Causal Impacts

3.3.4. Classification Accuracy/Error Measure

Bayesian networks are probabilistic models, and hence they render probabilistic predictions or probabilistic classifications. Validation metrics such as error rate and accuracy, which are ideal for classification schemes whose outputs are definitive as correct or incorrect without any grays, don't accurately measure performance of probabilistic models. In probabilistic prediction, it is natural to account for the probability value of each prediction in relation to the actual outcome. For instance, a higher probability of a correct classification should weigh more than that of a smaller one even when the latter is above 0.5. The most appropriate approach for scoring probabilistic models on the target concept is by penalizing predictors that make the worse guess on the true probabilities.

One of the commonly applied performance metrics for measuring the accuracy of probabilistic classifications is Brier score, (Brier, 1950). Brier score is a score function to measure the accuracy of probabilistic classification of binary and categorical variables. The score measures the calibration of the probabilities of each outcome of the variable. It measures the mean squared difference between the probabilities of the classification and the actual outcome over the sample instances. Therefore, smaller Brier score imply better classification accuracy. The proper scoring rule form of Brier is,

$$BS = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{R}(p_{ij} - o_{ij})^2$$

Where, R is the number of states in the class variable and N is the sample size

For binary variables, the alternative and widely used form is,

$$BS = \frac{1}{N}\sum_{i=1}^{N}(p_i - o_i)^2$$

As the o_i observations are binary, their values are either 1 when the event occurs or 0 if it doesn't. Since the Brier is score is a type of cost function, the goal is to minimize it, hence for a perfect prediction, the score is 0 and it is 1 for worst prediction.

3.4. Partial Structure Learning

The structures of all the networks that contain top causal factors are defined only partially. The identification of the top causal factors for each target event independently implies that there is a link between each causal factor and the target. However, we have yet to determine the correlations between the top causal factors which can only be achieved by applying a structure learning scheme. In general, structure learning is a more challenging problem, particularly when a large number of variables are involved. The following section describes the type of structure learning used for this problem and some of the reasoning behind choosing the learning algorithm.

3.4.1. Unsupervised Structure Learning

Most structure learning algorithms in use today are in the form of unsupervised learning, they don't separate the target variable from the attributes. They learn the network by trying to identify a set of structures that represent the probability distribution over the training dataset and take the best one using some kind of ranking (Friedman and Goldszmidt, 1996). Hence, such algorithms follow a kind of optimization process by incorporating search techniques, usually heuristic ones, over the space of available structures and using various scoring function to determine the best structure with respect to the training data. For most real world problems, the optimization process is intractable due to the large space of available structures. As a result almost all search and score-based algorithms apply restrictions to only cover certain classes of structures, for instance, using sampling, and can learn the "best" structure in polynomial time. One such heuristic-search algorithm is the K2 algorithm (Cooper and Herskovits, 1992), which applies certain ordering of the domain variables and each variable can only have a given maximum number of parents with respect to the ordering.

Search and score-based structure learning methods have theoretical justification in terms of their asymptotical correctness. Given a large set of independent samples, the learned structure is a close approximation for the probability distribution of the data generating process. However, in reality they could present a classifier with poor classification accuracy even though they may have relatively higher scores. Empirical analyses suggest that score-based structure learning occasionally results in inconsistent output, i.e. a network with a better score is not necessarily a better classifier (Friedman and Goldszmidt, 1997). There are multiple factors for the inconsistency of such results, such as the type of data, sample size, number of variables etc. However, the primary reason is the type of score function used. In their experiment, Friedman and Goldszmidt verified that a classifier based on the Minimum Description Language (MDL) score function performed poorly on many datasets involving more than fifteen variables. Almost all such learning methods involve feature selection by which they remove irrelevant variables which is mostly a very useful component of the classification process. However, occasionally, the feature selection process removes relevant variables which can have serious consequences in the classification performance.

In this research, the feature selection algorithm is done independently using algorithms described in previous sections. As a result, using the heuristic search and score approaches for the purpose of learning the partial structures has negative consequences. Based on experiments I have conducted using K2 and Hill Climbing to do the structure learning, both rendered less than optimal results. K2 provided none to very few correlations between the causal factors and Hill Combing resulted in excessively complex network on the twenty one event models and a total of eighty top causal factors.

3.4.2. Tree-Augmented Naïve (TAN) Bayesian Structure Learning

Despite its unrealistic strong independence assumption, naïve Bayes classifier has shown surprisingly good results in various domains. Naïve Bayes classifier learns the conditional probability of each attribute given the target variable, and the classification is done by applying simple Bayes rule; all the attributes are assumed to be independent given the target which makes it computationally very feasible. It considers all the attributes as relevant so as to determine the class of the target variable. In the context of probabilistic networks, attribute relevance is based on the notion of Markov blanket of a given variable. Markov blanket of a variable includes parents of the variable, its children, and the parents of its children (Pearl, 1988).

TAN is a structure learning algorithm which extends the naïve Bayes classifier, and it approximates the interactions between attributes by using a tree structure imposed on the naïve Bayes structure and is a polynomial time algorithm (Friedman and Goldszmidt, 1997). Experiments show that TAN performs significantly better on many dataset compared to C4.5 and naïve Bayes. The performance improvement of TAN in classifying the target variable is attributed to the fact that it gives special emphasis to the target variable by enforcing a link between the target variable and each attribute. For instance, applying the TAN learning scheme in the Runway Incursion network, because of the augmented edges, there exists a link between Crossing Active Runway and Hold Short Clearance causal factors signifying that the impact of Crossing Active Runway on Runway Incursion events is dependent on the influence of Hold Short clearance. Similar to other unrestricted search algorithms, discovering the set of augmented edges of TAN learning to determine the best structure is an intractable problem. As proposed by

Friedman and Goldszmidt, imposing acceptable restrictions on the structure in which the target variable has no parents and each of the attributes can have a maximum of one other attribute in addition to the target variable renders a polynomial time algorithm.

The principle of TAN structure learning is based on the notion of tree dependence to approximate n-dimensional probability distributions using maximum-likelihood estimation (Chow and Liu, 1968). A tree-based directed acyclic graph contains parentless target variable and attributes with a maximum of two parents, the target and one other attribute, and the tree building procedure involves finding a function over those attributes that maximizes the log likelihood of the structure. In the Runway Incursion model, for instance, the set of attributes are the causal factors $C_1, \ldots, C_n$ and the runway target event is E. In TAN structure representation, E has no parents ($\pi_E = \emptyset$) and there exists a function f that defines a tree over the causal factors $C_1, \ldots, C_n$ such that,

$$\pi C_i = \{E, C_{f(i)}\} \qquad \text{if } f(i) > 0$$

$$\pi C_i = \{E\} \text{ if } f(i) = 0$$

The TAN structure building algorithm proposed by Friedman and Goldszmidt, which is based on tree independence model of Chow and Liu, involves conditional mutual information between the attributes given the target variable.

$$I_P(\boldsymbol{X}, \boldsymbol{Y}|\boldsymbol{Z}) = \sum_{\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}} P(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) log \frac{P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{z})}{P(\boldsymbol{x}|\boldsymbol{z})P(\boldsymbol{y}|\boldsymbol{z})}$$

This relation measures mutual information based on the difference of entropy which is the information gain provided by $\boldsymbol{Y}$ about $\boldsymbol{X}$ given $\boldsymbol{Z}$. One is referred to Cover and Thomas (1991) for a comprehensive treatment of information theory and representation of the log likelihood score. TAN structure learning involves the following five main steps, 1) compute conditional mutual information (I_P) between the attributes given the target, 2) build a complete undirected graph with the attributes as vertices and the edges between them as I_P, 3) Build a maximum weighted spanning tree, 4) Transform to directed tree by making the target as the root of the tree, and 5) construct the final TAN model by adding the target vertex and linking it to each attribute. The TAN structure learning algorithm has time complexity of $O(n^2N)$ where n is the number of attributes and N is number of instances of in the data.

The Runway Incursion model in figure-26 shows the link association discovered by TAN learning between Take-Off and Surface Movement causal factors and between Hold Short and Crossing Active Runway causal factors. As described above, TAN results in a simpler structure than other learning schemes and yet provides better classification accuracy than naïve Bayes by removing the strong independence assumption between the attributes.

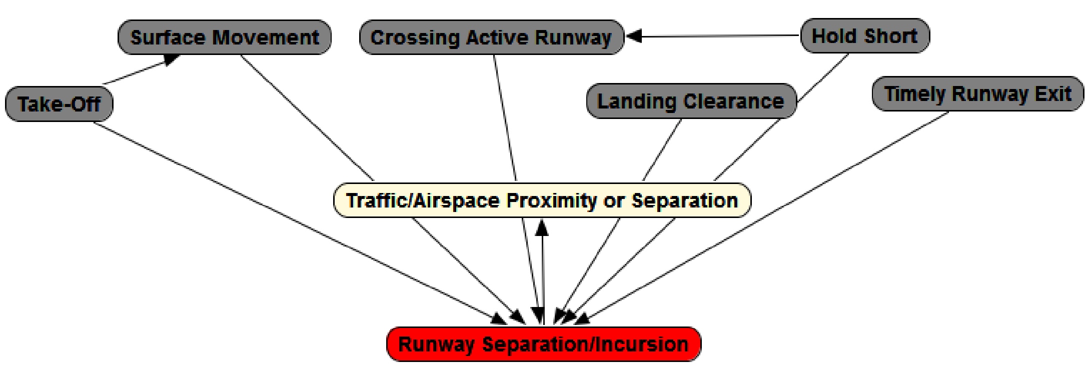


Figure 26: TAN Structure Learning for RI Model

3.5. Ranking of Common Factors

As described in prior sections, the identification of top causal factors is in relation to individual events, i.e. the algorithms rely on conditional probabilities of the causal factors given the particular event. As a result, although they provide critical information as to what factors contribute primarily to individual events, they don't specify about the generic issues in the NAS. Identifying common factors (generic issues) from data is so important to communicate safety issues to the public and officials who are not particularly concerned in the assessment of individual events but the overall risk in the NAS for the flying public. This section describes how the common factors can be identified from all the top causal factors that play a significant role in causing and contributing to all event types.

Most quantitative risk management processes involve identifying individual hazards and factoring the severity and occurrences or "likelihood" of those hazards. In aviation risk management, severity is a measure of the effect of any particular hazard on the safety of operation. It is measured by a numerical index to quantify the relative risk of each hazard. For instance, for the purpose of determining accident risk in the NAS, the FAA safety office uses a risk matrix based on five severity indices, 1- Catastrophic, 2-Hazardous, 3-Major, 4-Minor, and 5-Minimal. Each of these indices is determined in relation to its severity in different domains, such as the ATC services, flight operations, and the flying public. Occurrences on the other hand deal with the "likelihood" of a particular hazard in relation to some frequency measure. For instance, in aviation safety risk management, occurrence is defined as the ratio of the number of a given hazard to the number of operations or total flight hours for a specific time frame. The severity and the occurrence together are used to quantify the risk in relation to some baseline determined using domain knowledge. For the setting in this research, we can apply a similar concept to rank the common or generic ATC-related factors in the NAS from the top causal factors identified for individual events.

In this research, we deal with incidents instead of hazards, but each incident has associated severity index assigned to it. As a result we can't simply use number of operations as a "likelihood" measure since not every incident is a hazard to aviation safety. However, we can use the relative frequency of each causal factor given the severity index as a similar measure. Using *K* severity indices, relative frequency of a top causal factor, and the number of incidents from each category, the weight of each causal factor can be determined by the following measure,

$$F_i = \sum_{j=1}^{K} {}^{1}\!/_{SI_j}\, N_{ij}$$

In this expression, F_i is the ith factor, SI_j is the jth severity index, and N_{ij} is the number of events with jth severity that the ith causal factor is involved in. In this setting, we are assuming that every event regardless of its type is weighted equally as long as it is in the same severity class. That is, a Runway Incursion event has the same severity weight as a Wake Turbulence event if the two have the same severity classification. This assumption might not hold true in some cases as people tend to consider certain types of events as more serious and consequential than others even with the same severity index.

3.6. Relationships of Events and Top Causal Factors over Time

The sensitivity analysis and performance measure of each event model allow us to identify the current top causal factors based on historical data, in a sense it is the snapshot of the current causal factors for the given event. However, it doesn't tell us how the relationship between the top causal factors and the event behaved through time. In dynamic systems such as the NAS, the characteristics of the data change overtime reflecting the current state of the system. In standard Bayesian network learning we consider every record in the training set with equal weight which comes from the assumption that our observations have been produced by a stationary stochastic process. For networks in dynamic problems we need to introduce a mechanism to adapt to the changing system. One way of simulating a changing environment is using adapting learning (Nielsen & Nielsen, 2008) by relaxing the assumption of stationary data to piecewise stationary. Another simpler approach of adaptation which can be achieved at the parameter estimation level is through the use of fading which involves assigning different weight factors for training cases based on time. Using smaller weights for past experiences and higher weights for recent observations we can make the model represent more the current state of the system.

In this research I apply a different technique to gauge the extent to which the data generating process has been changing for each undesired event. Using the top causal factors identified from the full dataset, I export a weighted impact of each factor over time. The data output used for this analysis maybe the monthly or quarterly distribution of the top causal factors along with the impact, which is the change of probability as a result of providing evidence on the undesired event, as a weight. For instance, for n top causal factors $\{C_1, C_2, \ldots., C_n\}$ and the impact of each as weights $\{w_1, w_2, \ldots., w_n\}$, the weighted average of the top causal factors is given by,

$$\bar{C_i} = \frac{w_i P(C_i)}{\sum_{j=1}^{n} w_j}, \qquad where\ w_i = P(C_i|E)$$

The mean of the monthly weighted averages gives us the aggregate of the causal contributions of the n causal factors at different times. Similarly, the monthly/quarterly distribution of the undesired event can be calculated as a proportion of the whole events reported in a given month/quarter. We can apply time series analysis and/or regression to analyze the strength or weakness of the relationships between the aggregated causal factors and the undesired event through a specified time period to understand the effect of the change in the system on the distribution of the causal factors and the event. For instance, for Runway Incursion and its six top causal factors the monthly moving average and the seasonally adjusted time series plots are shown below.

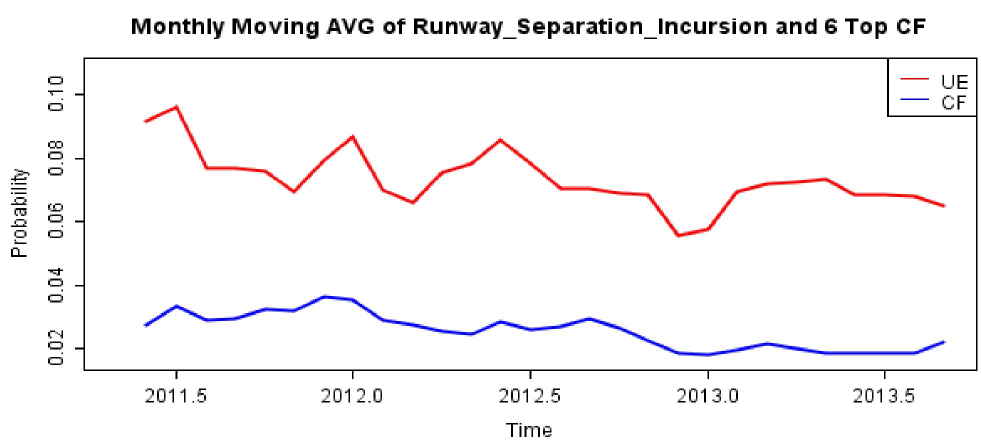


Figure 27: Time Series Plots of RI & Mean of Top Causal Factors

The time series plots indicate that there hasn't been a significant deviation in the relationship between the causal factors and runway incursions in the past two years.

Alternatively, the causal-effect relationship of the top causal factors and the undesired event can be visualized using a scatterplot. The following scatterplot with the mean causal factors on the x-axis (control parameter) and the undesired event on the y-axis along with regression line and a smooth curve depicts the correlation (causation).

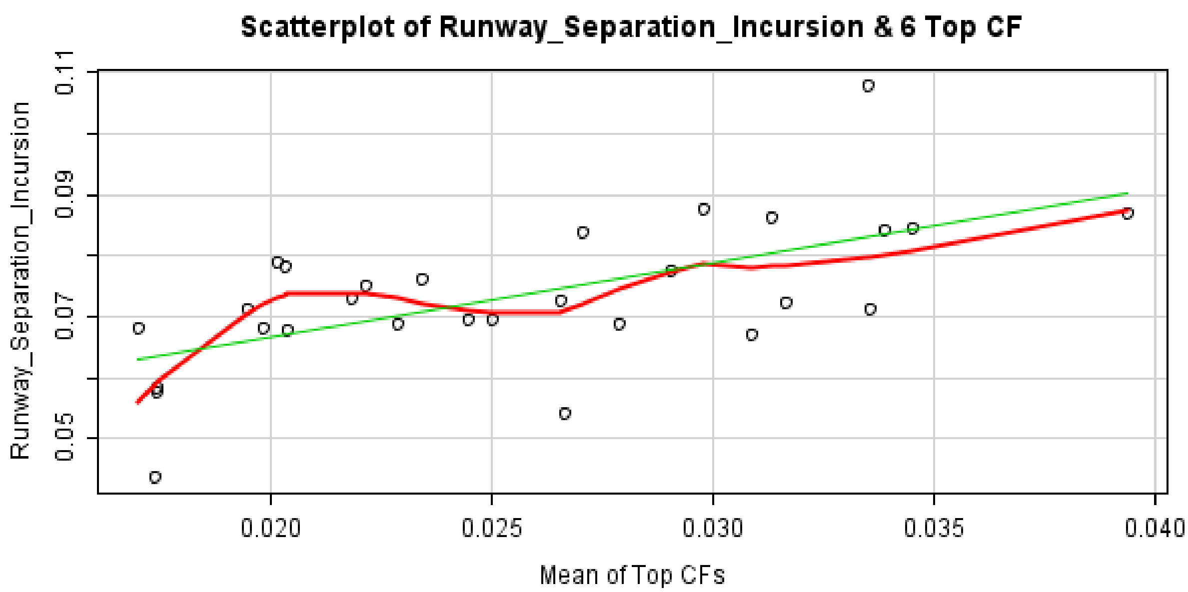


Figure 28: Scatterplot of RI vs. Aggregate of Top Causal Factors

The green line is a simple linear regression fit assuming that there exists a linear relationship between the aggregate of the top causal factors and the probability distribution of the undesired event. In linear regression, a straight line is fit to the data points by minimizing the sum of the residual, vertical distance between fitted line and the data set. The red curve is the output from LOESS function which is a nonparametric-regression smoother using local fitting. In LOESS, a low-degree polynomial is fitted using weighted least squares at each data point by assigning more weights to the closer points. Similar to the time series plots, the scatterplot indicattes the existence of a correlation between runway incurssion and its top causal factors.

3.7. Top Causal to Causal Relationships

One of the primary purposes of identifying top causal factors for each event type is to intervene in the system by taking actions such as placing technological solutions, introducing new procedures, providing proficiency training to employees etc. Occasionally, however, it is difficult to directly affect some causal factors, for instance, there are very little measures to be taken to affect weather factors directly. In those cases where the causal factor is non-actionable, one would like to know other causal factors that are highly correlated with the top factor of the undesired event. By identifying those strongly associated causal factors and taking measures to reduce their likelihood, it is possible to indirectly affect the unwanted event being considered in the event model.

Model creation of the causal-to-causal networks are exactly similar to the standard Bayesian network learning from data. We include the n number of associated causal factors with the target causal factor as nodes and the parameters are estimated from the training dataset. The automated model builder for this research creates unique causal-to-causal factor models for each primary causal factor in each event type the number of which is determined by the custom parameters set before launching the tool. Figure-29 shows a superimposed causal-to-causal model for “Timely Runway Exit” primary factor from a runway incursion event model. As a result, even though it may be impossible to directly tackle timely runway exit causal factor, it may be possible to minimize its occurrence by taking measures on the other associated causal factors regardless of their direct involvement in the event considered in the primary event model.

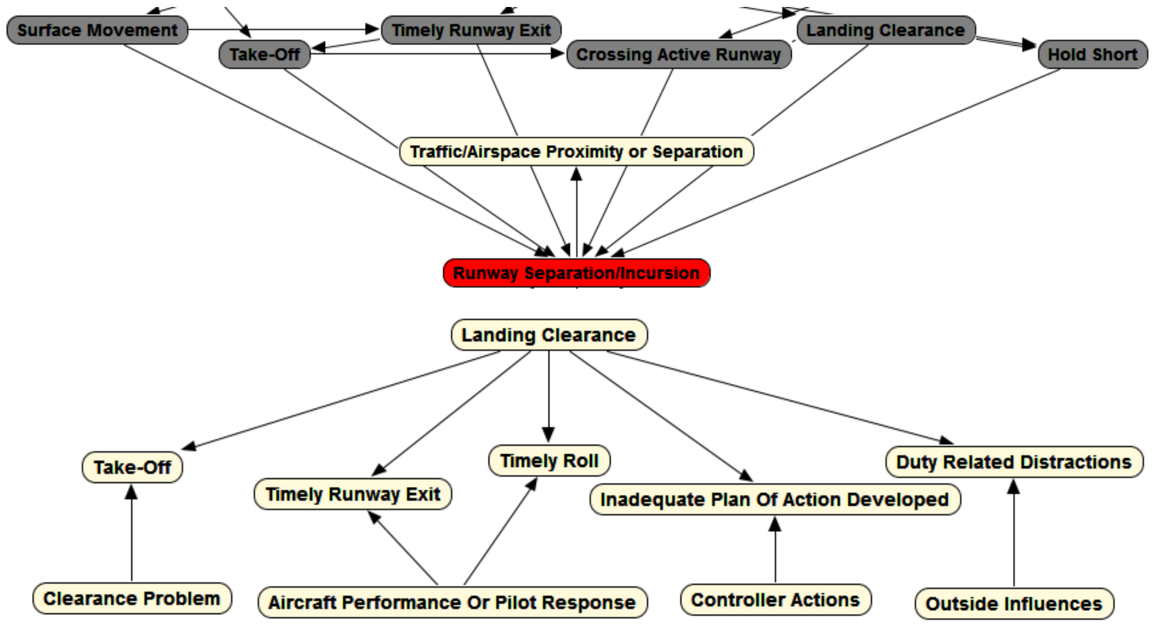


Figure 29: Superimposed Causal-to-Causal Network for Landing Clearance

In this particular model most of the associated causal factors to the target factor happen to be also the primary causal factor for the event.

3.8. Decision Analysis

Decision analysis is a discipline about the evaluation of various decision alternatives in a given problem and the values of those outcomes as a result of the decisions in the presence of uncertainty. The primary goal of engaging in decision analysis is in order to reach at optimal and "rational" decisions. Effective decision making involving complex problems is an important and difficult task. In probabilistic models, we are concerned not only about the outcome of our actions but also the amount of risk those decisions carry as a factor of the uncertainty. The fundamental concerns of decision analysis are weighing the probability of an event and the value of the probabilistic outcome of our actions in relation to the event to determine the consequence of our choices.

Various techniques and mathematical models are used in decision analysis to maximize the value of the outcomes as a consequence of our decisions. Such models are comprised of different components such as the events which are governed by nature, the circumstances under which the decision are made, the set of actions, and the final outcome or return of the interactions of those components. Each component has a source of error which contributes to the uncertain outcome of the decision making process. Some of the sources of errors are, partial understanding of the circumstances, incorrect assumptions, the utility function used to measure the value of each outcome, and forecasting errors.

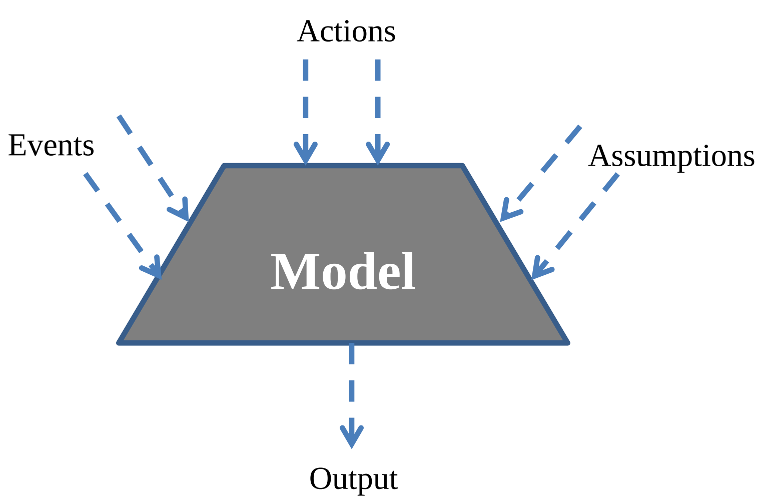


Figure 30: Components of a Decision Model

The domains of most mathematical decision models fall between two extreme ends based on our level of knowledge in the problem domain and the circumstances that govern it. On one end we have a pure uncertain model as a result of our complete ignorance and on the other end we have a deterministic model due to our complete knowledge. What lie in between are most models which are probabilistic due to our partial knowledge.

3.8.1. Causal Bayesian Networks

The only requirement in standard Bayesian networks is that the structure needs to represent the underlying joint distribution correctly and answer probabilistic queries. The direction of links between nodes in standard Bayesian networks don't need to encode causality, they may only represent correlations. When the directions of links are significant, Bayesian networks can encode the causal relationship of one variable to another and such networks are called causal models. In causal Bayesian networks, the value of each variable is probabilistically governed by the values of its parents. For instance, in our Runway Incursion model, take-off clearance is a causal factor to RI event and such relationship is depicted by the fact that the direction of the link is towards the effect variable.

Without some level of domain knowledge identifying causality is generally a challenging problem. Given two correlated variables X and Y, it may be the case that X causes Y, Y causes X or both may be correlated as a result of one or more external observable or unobservable variables acting on them. For the purpose of answering probabilistic queries, it is not necessary that we need to explicitly encode the unobservable variables as long as the model captures the marginal distribution over the observable variables. However, in causal model we need to identify the true source of the cause for an effect in order to answer causal queries.

3.8.2. Intervention in Causal Models

Causal models lend themselves to intervention which refers to an action taken to force one or more causal variables to take a certain state. When we intervene and do actions to force variables take certain values as opposed to observed values, the intervention queries are explained using 'do-calculus' which is due to Judea Pearl, (Pearl, 1995). For instance, when we intervene in the RI causal model, we may take some measures and fix take-off clearance problem and force its state to be "Not Factor" signifying that it is no longer a cause for the target event. This results in a different network from which the take-off causal factor is removed and the intervention query is done as follows.

$$P(RI \mid do(fix(TC), SMC, TRE, ..) = P(RI \mid SMC, TRE, ..)$$

In the above expression the assumption is that the causal relationship between take-off clearance and RI event is entirely due to the correlation between the two variables, i.e. there are no other hidden variables that are common to them and contribute to their correlations. However, if we don't assume that no hidden causes exist for the causality, answering intervention query involves disentangling the effect of the hidden variables which is generally a more difficult task. Pearls 'do-calculus' deals with actions that result in a forced state with probability 1.0, perfect interventions. In reality, however, fixing a take-off clearance may involve taking multiple actions and each of such actions results in a certain level of reduction in the likelihood of the occurrence of the RI event.

3.8.3. Utilities in Decision Making

In a decision making setting, there may be one or more possible actions with different degrees of preferences by the decision maker and each action leads to a different set of outcomes. In simple cases, each action results in one or more outputs with certainty, and the appropriate action is selected in relation to the preferred outcome. However, in real world problems, outcomes of an action or set of actions result in complex set of outcomes distributed probabilistically. As a result, we need a numerical measure to give a relative weighting of the different outcomes according to our preferences, a higher weight to a preferred outcome and a lesser one to least preferred outcome. In decision theory, the formal metric to measure such weighted outcomes is a utility function.

The utility of an outcome is the numerical value of the outcome and a utility function maps an action to a numerical value. In general, the higher the value of the outcome, the preferred the action that leads to that outcome is. Numerical utilities allow us to aggregate various probabilistic outcomes in order to reach the most preferred action. In most practical decision making, the numerical utility values are significant and are used to measure the relative strength of each outcome and such utilities are called cardinal utilities. In ordinal utilities, we are not concerned about the relative numerical values of each utility; we are merely interested in some kind preference ordering. The probabilistic outcome of an action or set of actions are combined using expected utility and the actions are ranked according to their expected utilities.

3.8.4. Utility Functions

The use of utility in decision theory originated from economics, and it refers to the perceived value of a good. In any utility-based decision making process, it is the numerical value of the outcome of a decision. We need a mathematical function to map the different outcomes as a result of our preferred decision choice to a numerical value. Such functions are called utility functions and they are measurable functions on a probability space. Although the use of utility function was suggested first by Bernoulli in 1738 to solve the St Petersburg Paradox[1], the theory and the associated axioms of utility function were further developed by von Neumann and Morgenstern in 1944. A utility function $U : X \to \mathbb{R}$ is defined as,

Let $\boldsymbol{X}$ be a set of preferences, $\gtrsim$ be preference relation, i.e. x $\gtrsim$ y implies that x is the preferred choice or the decision maker is indifferent between x and y,

For decision making in one variable,

$$\forall x, y \in X, x \gtrsim \mathrm{y} \iff \mathrm{U(x)} \geq U(y)$$

For decision making in multiple variables,

$$\forall (x_1, \dots, x_n), (y_1, \dots, y_n) \in \boldsymbol{X},$$

$$(x_1, \dots, x_n) \gtrsim (y_1, \dots, y_n) \iff \mathrm{U}(x_1, \dots, x_n) \geq U(y_1, \dots, y_n)$$

An important characteristic of a utility function is that it is an increasing function, the higher the utility value the preferred the decision that leads to that output is.

[1] A game of chance in which a fair coin is tossed repeatedly and a single player pays some fee doubling every time a head appears. The game ends, and the player wins when a tail appears.

$$U'(x) > 0$$

However, after achieving certain level of utility values, the utility increase is smaller making the utility curve concave, and such phenomenon is called decreasing marginal utility.

$$U''(x) < 0$$

In minimizing the likelihood of decreasing an undesired event, for instance, the actions we take on the various causal factors have higher effect (higher utility) towards the initial stages of our actions than the final stages. Once we achieved a level of event reduction, our actions in addressing more causal factors have lesser effects and it is unlikely that we can completely eliminate the chance of event occurring due to other external factors that are not directly attributable to factors we have direct control over.

3.8.5. The Effect of Risk on Utility Function

Decision makers always need to take into consideration the risk involved when arriving at a decision. A situation in which there are potential life loss and public safety risks is taken much more seriously than a situation where only financial losses or gains are in play. Also, evaluating the decision and determining the utility of each outcome in high risk situations are much more difficult. Some of the models in this research involve potentially high risk events such as serious runway incursions, loss of separations, operational deviations etc. that could lead to potential accidents. However, for the purpose of making decisions, the risks involved in this setting are not only related to the severity of the event, they also involve the amount of scarce resources needed to be allocated to minimize the likelihood of the undesired events. As a result, the utility evaluation in this setting should weigh the risk of implementation of placing system or procedural changes, mitigation strategies, and the risk of events occurring, severe and less severe.

In the presence of risk, the selection of the utility function depends on the level of risk aversion or risk seeking the decision makers would like to assume. As a result, there is no single utility function that satisfies the preference of every decision maker even under the same circumstances. However, in applying expected utility maximization, it is assumed that every decision maker acts rationally in accordance with the four axioms of utility theory.

The most common utility function in the presence of risk is exponential function primarily due to its convenience in the computation.

$$U(x) = -e^{-\alpha x}, \alpha > 0$$

Computing the expected utility using an exponential utility function is equivalent to calculating the moment generating function of a given variable. For instance, assume that the allocated monitory resource to resolve one of the causal factors, R, as a random variable and the decision maker uses exponential utility to measure the outcome in the reduction of the event.

$$\mathrm{E}[U(R)] = -\mathrm{E}[e^{-\alpha M}] = -M_R(\alpha)$$

Assume that allocating increasingly more resources to resolve a causal factor will reduce a given undesired event. As a result, the more resource we allocate, the higher the utility becomes. However, after a certain level of reduction of the undesired event is achieved, allocating more resources in addressing the same causal factor has increasingly lesser effect in the reduction. Consider a situation where we can reduce a certain undesired event by allocating resource X_1 on one of the top causal factor with probability α. Also consider we can achieve a higher reduction of the event by allocating more resource X_2 on the same causal factor with probability $1-\alpha$ as shown in the utility curve below.

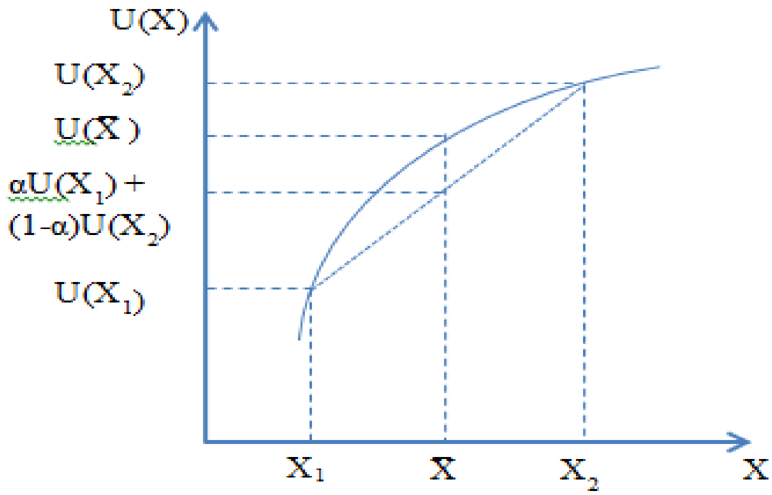


Figure 31: Utility Curve with Risk Level

The expected value of the two outcomes is,

$$\alpha X_1 + (1 - \alpha)X_2$$

The utility of $\bar{X}$ in the above graph is greater than the utility of the expected value of the resource allocation, hence the decision maker would prefer$\bar{X}$. Such concave utility function controls the marginal utility changes, and help determine how the decision maker acts under risk, and it is called risk aversion. Utility-based decisions that follow a linear curve are called risk-neutral and those that follow convex curves are known as risk-seeking. However, most utility curves are linear locally and assume risk neutrality for sufficiently small risk and benefits.

3.8.6. Expected Utility

An action can have multiple consequences or outcomes based on the realization of the target event. In "rational" decision making, the desired outcome can be achieved by maximizing the expected utility in which the utility value of each outcome is measured using utility function and the realization of the event is distributed probabilistically. The theoretical justification for using the principle of expected utility as a definition of "rational" behavior of the decision maker is rooted in the axioms of utility (von Neumann & Morgenstern, 1944). According to utility theorem, for a decision maker who abides by the axioms, there exists a utility function such that his or her decision is equivalent to the maximum expected utility relative to the utility function. The four axioms of utility theory are,

Completeness: for outcomes o_1 and o_2, the decision maker must be able to prefer one, two or consider them equivalent.

$$o_1 \succ o_2 \mid o_1 \prec o_2 \mid o_1 \sim o_2$$

Transitivity: for outcomes o_1, o_2, and o_3, if the decision maker prefers one to two and two to three, he also prefers one to three.

$$o_1 \succ o_2 \;\&\; o_2 \succ o_3 \Rightarrow o_1 \succ o_3$$

Continuity: for outcomes o_1, o_2, o_3 and probability α, if the decision maker prefers one to two and two to three, then there is a possible combination of one and three with equal preference with two.

$$o_1 \succ o_2 \succ o_3 \Rightarrow o_2 \sim [o_1\!: \alpha;\ o_3\!: (1-\alpha)],\ \alpha \in (0,1)$$

Independence: for outcomes o_1, o_2, o_3 and probability α, if the decision maker has equal preference for one and two, then the third can be combined with either without changing the preferred outcome.

$$o_1 \sim o_2 \Rightarrow [o_1\!: \alpha;\ o_3\!: (1-\alpha)] \sim [o_2\!: \alpha;\ o_3\!: (1-\alpha)]$$

The central theme of expected utility principle is that the highest expected utility as opposed to expected value is used as the basis for the preferred outcome. Therefore, for n possible outcomes *O* of an action *A* the expected utility EU is the sum of the product of the utility function and the probability of each outcome.

$$EU = \sum_{i=1}^{n} (U(O_i|A)P(O_i|A))$$

It is expressed as a linear combination of the utilities of each outcome where the weights are given by their respective probabilities. In the runway incursion model, for instance, the possible alternative actions are, full control, partial control, or no control of one of the causal factors, and the possible outcomes are reduction of runway incursion and no reduction in the occurrence of runway incursions.

3.8.7. Graphical Representation of Decision Analysis

Decision network, also known as influence diagram, is a structured representation of a decision making process, it is an extension of a Bayesian network. It is a directed acyclic graph consisting of three types of nodes—chance, decision, and utility nodes. Like a Bayesian network, the chance nodes represent the random variables and their values are governed by nature. The values of the decision nodes are directly controlled by the decision maker reflecting his/her choice of preferences among the competing alternatives. Finally, there are deterministic and numerically valued nodes to encode the output of the utility function. Unlike nature and decision nodes, utility nodes can't have any children. In most standard graphical representation of decision networks, the nature nodes are represented by ovals, the decision nodes by rectangles, and diamonds represent the utility nodes.

For a decision variable in the network, there are one or more variables whose values the decision maker need to know in order to prefer a certain choice. In graphical network representation, such set of variables are modeled as parents to the decision variable with edges going into it. Thus, the decision rule provides values for each possible combination of the parent variables so as to enable the decision maker choose the best outcome, making the decision process a local conditional model for individual decision variables.

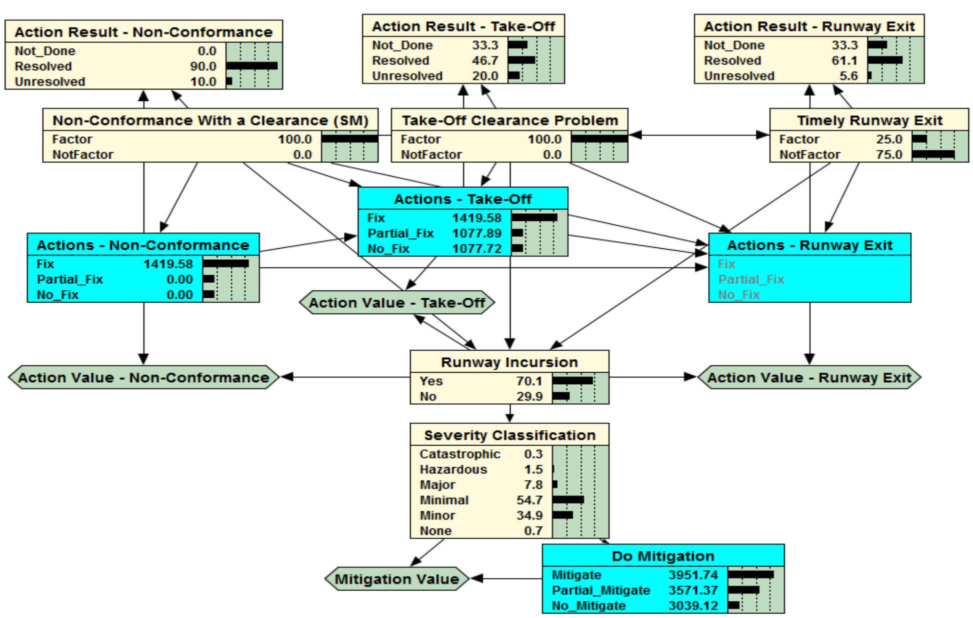


Figure 32: Runway Incursion Decision Network

Figure-32 shows a decision network to minimize runway incursion using its three top causal factors. The three nodes at the top layer of the diagram are the control variables to the three causal factors leading to the runway incursion event.

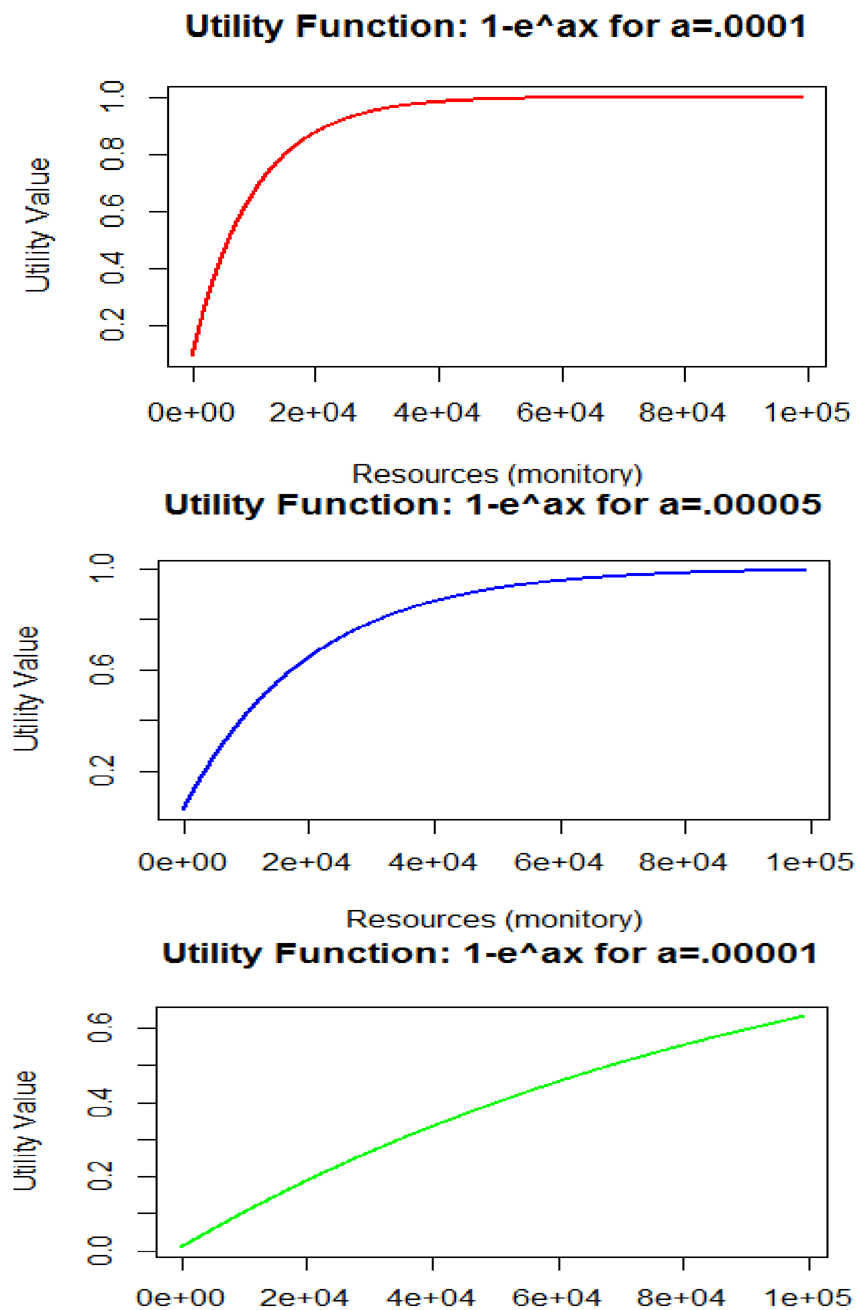


Figure 33: Utility Functions for Runway Incursion Model

The control variables are functions of the result of the three serial actions, cyan nodes, of the decision maker and distribution of the causal factors. The green diamond nodes are the utility nodes to measure the probability of the Runway Incursion event and the choice of the decision maker on the action nodes.

Similarly, we have a utility node and an action to the mitigation variable to affect the consequence of the incident in the event it occurs. The functions to measure the utility of each output as a result of our actions are shown in figure-33, they are meant to be experimental values. In actual decision making those values are determined based on additional factors that are available to the decision maker.

3.9. Automated Model Creation

In large networks, creating the DAG and the local CPDs manually can be very tedious. Although there are various packages with easier user interfaces for creating nodes, connecting edges, and entering the local CPDs, building large networks manually can still be very laborious task. For this project, I have compiled various software packages such as, R, WEKA, NETICA, and connected them using a custom java program that generates the network and the various components of the models explained throughout this paper without the need to manual interventions. An XML-based configuration file, which is exported from the database schema, contains information such as the name of the variables, parent variables, relative location, and the hierarchal structure entirely reflects those relationships. The CPDs for each variable are populated from the training data file using frequency count, and the performance is validated against the test dataset.

4. RESEARCH ANALYSES

This section describes the results of an analysis using the algorithms described in chapter 3 (Methodology) on the ATSAP data. The analysis was conducted using ATSAP data from May 2011 to October 2013. This period coincides with the ATSAP taxonomy structure that includes 21 event types and more than 300 causal factors. The incidents are classified under three categories: Proximity/Separation Issues, Unexpected Conditions, and Aircraft Accident, and the factors are grouped into 15 high-level categories. The various causal models were trained using 35,000 event records that comprise a total of 41,000 incident reports. Although the large majority of events are distinct events, there are some overlaps between separation and unexpected condition events. That is, some separation problems also involve unexpected conditions. Consequently, it is required that we treat each event as a separate Bernoulli variable for the purpose of identifying its causal factors and their correlations given the event.

This section is organized as follows: section 4.1 summarizes the list of events with their relative frequency and severity. Section 4.2 summarizes the significant causal factors for each event as identified by the probabilistic causal models. Section 4.3 explains some of the reasoning behind the high variations in correlation between significant factors and few of the events over time in. Section 4.4 describes the top-n issues as determined by a ranking algorithm. Section 4.5 describes the causal-to-causal relationship models to analyze non-actionable factors.

4.1. Severity & Relative Frequency of Events

A critical variable for measuring the impact of each causal factor in relation to different event types is the severity of the event. The severity along with the frequency of a causal factor in incidents determines the ranking of the factor (section 3.3). Each event is assigned one of the six severity indices (0 to 5), which range from a simple non-safety issue to a catastrophic accident or potential accident. Table-2 shows the breakdown of the proportion of each event into the six severity classifications and the relative frequency of the event in the overall incident distribution.

Table 2: List of Events by Relative Frequency & Severity

Event Type	Relative Frequency	Catastrophic	Hazardous	Major	Minimal	Minor	None
IFR To IFR	0.3813	0.0002	0.0107	0.1241	0.5395	0.3171	0.0083
Adjacent Airspace	0.2751	0.0006	0.0028	0.0138	0.9218	0.0572	0.0038
Unsafe Situation	0.1447	0.0044	0.0157	0.0633	0.7140	0.1837	0.0190
Altitude	0.1350	0.0031	0.0091	0.0943	0.6813	0.2059	0.0062
Course/Routing	0.1243	0.0007	0.0092	0.0648	0.7442	0.1720	0.0092
Runway Separation/Incursion	0.0739	0.0017	0.0171	0.0742	0.4923	0.4084	0.0063
TCAS RA/Evasive Action	0.0498	0.0008	0.0295	0.6147	0.2007	0.1518	0.0025
VFR To IFR	0.0452	0.0028	0.0409	0.3126	0.4447	0.1842	0.0149
Go Around	0.0416	0.0020	0.0151	0.1372	0.4813	0.3582	0.0061
Wake Turbulence	0.0406	0.0010	0.0258	0.0610	0.4184	0.4835	0.0103
Terrain/Obstruction	0.0388	0.0130	0.0097	0.0443	0.2822	0.6357	0.0151

Speed	0.0368	0.0046	0.0080	0.0547	0.6180	0.2976	0.0171
Equipment Issue	0.0367	0.0171	0.0137	0.0389	0.8034	0.1143	0.0126
Aircraft Emergency	0.0181	0.1415	0.1369	0.1206	0.3457	0.2506	0.0046
Aircraft Accident	0.0123	0.5608	0.1115	0.0946	0.1385	0.0878	0.0068
NORDO/NORAC	0.0121	0.0069	0.0103	0.0655	0.6690	0.2414	0.0069
VFR To VFR	0.0099	0.0209	0.0460	0.0962	0.5816	0.2343	0.0209
Vehicle/Pedestrian	0.0095	0.0130	0.0087	0.0609	0.5478	0.3522	0.0174
Pilot Declared NMAC	0.0038	0.0106	0.3298	0.2872	0.1702	0.1809	0.0213
Spillout/Whiskey Alert	0.0033	0.0120	0.0120	0.0723	0.7590	0.1325	0.0120
Aircraft Security Event	0.0024	0.0164	0.0328	0.0656	0.7541	0.0656	0.0656

As can be seen in table-2, with the exception of events that involve accidents, the large majority of incidents are categorized either “Minimal” or “Minor” in their severity. Also, events with large proportion of the more severe categories have in general low relative frequencies. For instance, Aircraft Accident constitutes over 56% of catastrophic events, however, the relative frequencies of accidents given all event distributions is only about 1.2%. In other words, severe incidents such as catastrophic and hazardous are rare occurrences.

The computed relative frequencies which are displayed in table-2 for each event are calculated using marginal probabilities over all the top causal factors in the probabilistic model, they are not ratios of the direct frequency counts. As a result, there is usually a slight difference between the two values, ranging from 1/1000 to 7/1000, which is too small to affect the accuracy of the probabilistic models. Events are listed according to their relative frequencies without regard to the distribution of their severity, that is, events with higher frequencies are listed first. Also, few of the events in the bottom list have very small relative frequencies and hence the top causal factors identified for such events are less reliable due to the number of incidents available to train the models. As a result, events whose relative frequencies are less than 1% are excluded from the model outputs in section 4.2. Accidents are also excluded from the result due to some of the issues many raise as to whether or not the ATSAP program has the resources to analyze accidents. FAA regulation requires that aviation accidents are investigated and analyzed by the NTSB, and such investigation usually take longer time and much more resources.

4.2. Significant Causal Factors

This section describes the outputs of the probabilistic causal models that are generated to identify top causal factors for each event. The top causal factors are based on individual events, i.e., they are factors which are significant in causing or contributing to the individual safety events. As explained in sections above, the ranking of the causal factors are based on the difference of prior probabilities and posterior probabilities of each causal factor given a particular event. The larger the difference is the higher the ranking of the factor. In addition, correlation between any pair of causal factors given the learned structure of the network is indicated by a link between them with the direction of the link signifying no causality between the pairs. The correlation between factors is a result of the TAN structure learning described in partial structure learning section of chapter 3. The output includes a list of the top causal factors, probabilistic networks, time series plots, and scatterplots of the 15 events with computed relative frequency above 1%.

The tables show the listing of the significant causal factors for each event along with the definition of the causal factor as adapted from the ATSAP data dictionary, the prior probability which is the probability of the causal factor given all event types, and the posterior probability which is the probability of the factor given the particular event type. The posterior is calculated using message passing-based evidence propagation algorithm of Bayesian networks (see section 2.3.8). The probabilistic networks are represented in graphical models with incidents as target event variables, the factors (features) as causal nodes, and the links that connect any pair of nodes with significant correlation as determined by the structure learning algorithm. They also display the probabilistic values of each causal factor to indicate the strength of the correlation. The time series plots are used to assess the relationship of the aggregate of the top causal factors and an event frequency over a two year period (2011 – 2013). The scatterplots show visually the strength of the correlation of the aggregate top causal factors and event frequencies. When there are relatively many diverging variations between the aggregate factors and the event frequency, the relationship tends to be weaker which is shown on a non-increasing curve on the scatterplot (see section 4.3 for explanation).

4.2.1. IFR to IFR

IFR (Instrument Flight Rules) to IFR events are those that involve loss of standard separation between two or more aircraft operating under IFR rules. In IFR rules, flying by visual references are unsafe, and hence onboard instruments and electronic signals are used for navigation. There are 6 significant causal or contributing factors for IFR to IFR events as shown in table-3. The structure of the probabilistic model shows that there is a relatively stronger correlation between “altitude clearance problem” and “action or plan execution”. The time series plots between the aggregate of the top causal factors and the event show that since mid-2012, the two are diverging suggesting that other factors, not discovered in the model, were also playing role in causing or contributing to IFR to IFR events. Similar to the time series plots, the scatterplot shows that there is a decreasing correlation between the top causal factors identified and the event. If the trend continues, a similarly built model will show a different set of top causal factors in the near future.

Table 3: IFR to IFR Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Clearance Problem/Altitude	Issuing instruction other than what was authorized or intended	0.174	0.263
2	Controller Actions/Action or Plan Execution	Execution of a particular action and/or plan is poor/inadequate for the situation	0.183	0.255
3	Controller Actions/Inadequate Plan of Action Developed	Risk was not recognized or misjudged and the devised action or plan by the individual is inadequate for the situation	0.134	0.195
4	Clearance Problem/Heading	Issuing a heading instruction other than what was authorized or intended	0.08	0.138
5	Aircraft Performance or Pilot Response/Timely Aircraft Descent or Climb	The combined performance of the aircrew and the aircraft capability results in an untimely descent/climb	0.077	0.125
6	Aircraft Performance or Pilot Response/Timely Aircraft Turn	The combined performance of the aircrew and the aircraft capability results in an untimely turn	0.059	0.099

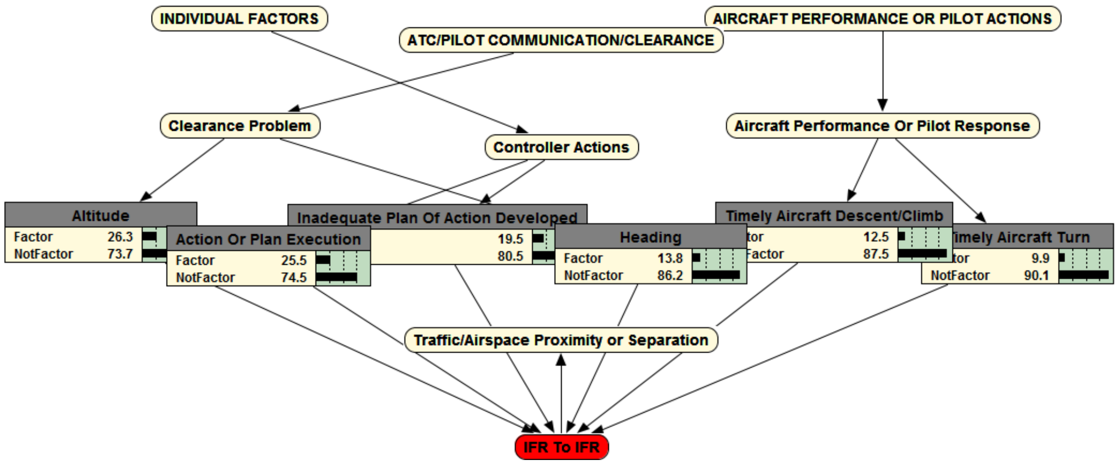


Figure 34: IFR to IFR Probabilistic Network

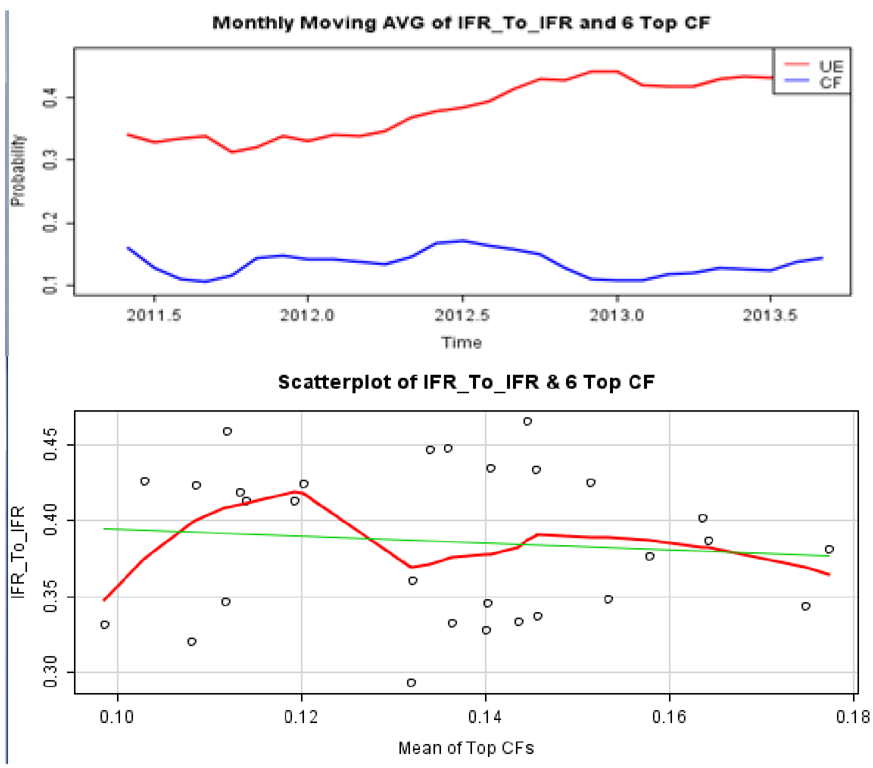


Figure 35: IFR to IFR & Top Causal Factors Correlation

4.2.2. Adjacent Airspace

Adjacent airspace events are separation issues surrounding adjacent airspace with another Air Navigation Service Provider (ANSP). The 7 significant causal factors identified by the model include issues such as controller actions, information exchange, outside influences, and airspace issues involving international providers. The structure of the model shows a stronger relationship between "duty-related distractions" and "auditory or visual information misinterpretation" causal factors. The time series plots show that there is relatively consistent relationship between the aggregate of the top causal factors and relative frequency of the event for the two years period plotted. This fact suggests that the same factors have been playing major role in causing or contributing to adjacent airspace events. The relatively stronger correlation shown by the scatterplot between the aggregate top causal factors and relative frequency of the event is a confirmation to what is displayed in the time series plots.

Table 4: Adjacent Airspace Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Controller Actions/Auditory or Visual Information Misinterpretation	Action towards a particular situation is the result of misinterpreting an auditory cue	0.155	0.206
2	Information Exchange/Flight Level	Intra/inter facility exchange of information involving flight level, or lack thereof, between controllers	0.058	0.099
3	Outside Influences/Duty Related Distractions	The individual was distracted by a competing operational concern	0.114	0.148
4	Information Exchange/Approval Request (APREQ)	A controller's request to deliver an aircraft to another sector other than standard operating protocol	0.044	0.077

5	Controller Influences/Over Relying on Automation	Becoming dependent on automation and is unable to safely complete a task without automation	0.019	0.048
6	Information Exchange/Route of Flight	Intra/inter facility exchange of information involving route of flight, or lack thereof, between controllers	0.039	0.063
7	Airspace/Adjacent Airspace, International Providers	Any issue that surrounds the involvement of another Air Navigation Service Provider's (ANSP) adjacent airspace	0.019	0.042

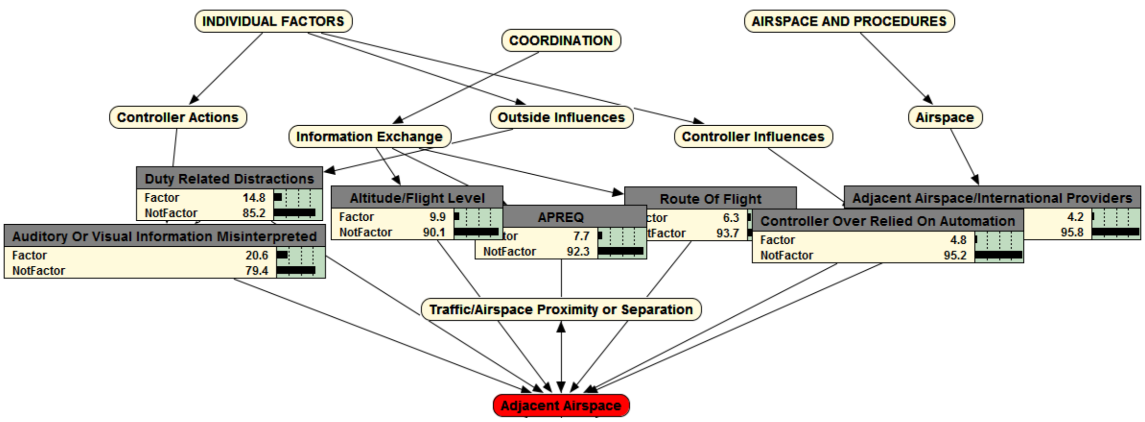


Figure 36: Adjacent Airspace Probabilistic Networks

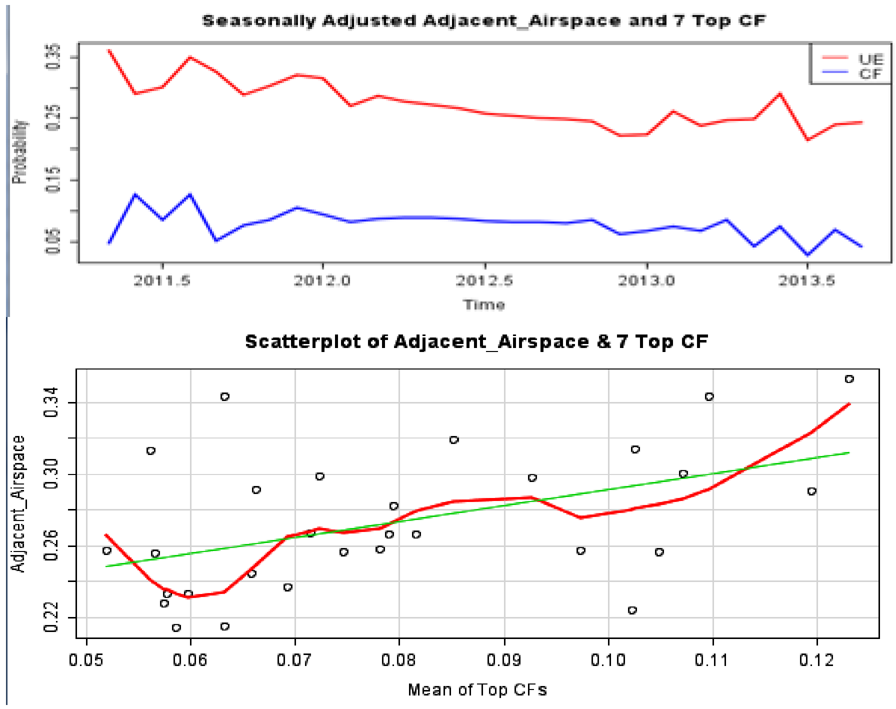


Figure 37: Adjacent Airspace & Top Causal Factors Correlation

4.2.3. Unsafe Situation

Unsafe situation is a safety risk that is of unexpected condition in nature. It is a generic issue that doesn't fall into any of the known event types. The 8 significant causal and/or contributing factors that are responsible for most of ATC-related unsafe situations include organizational, policy/procedures, and clearance issues. The structure of the network shows a relatively stronger correlation between "organizational lack of safety culture" and "procedures deficiency". A weaker relationship exists between the aggregate of the top causal factors and the event relative frequency. A weaker relationship is an indication that the causal factors are not consistent, that is, occasionally other causal factors play role in the event but they are not strong enough to be part of the significant factors. The weaker correlation between the aggregate top causal factors and the event frequency is also shown in the scatterplot.

Table 5: Unsafe Situation Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Organizational Influences/Inadequate or Lack of Safety Culture	The unofficial or unspoken rules, values, attitudes, beliefs, or customs of an organization undermine safety performance	0.033	0.083
2	Procedures/Deficiency	A deficient procedure	0.062	0.111
3	Non-Conformance with a Clearance/Surface Movement	A pilot/aircrew incorrectly executes the provisions of a taxi instruction	0.035	0.077
4	Facility Influences/Information Flow	When a breakdown in communication or exchange of information from leadership	0.027	0.069
5	Supervisory Influences/Safety or Risk Assessment	Leadership does not adequately recognize, evaluate, and manage the risks associated with a situation or task	0.02	0.062
6	Supervisory Influences/Unrealistic Expectations	Leadership fails to accurately assess an individual or teams capabilities to accomplish a task	0.035	0.074
7	Policy, Procedure Influences/Inadequate Policy or Procedure	Group leadership provides inadequate expectations for policy or practice	0.033	0.071
8	Policy, Procedural Deficiency/Facility Level	Lack of, inadequate or out of date presentation of facility operational information to personnel by group leadership	0.03	0.064

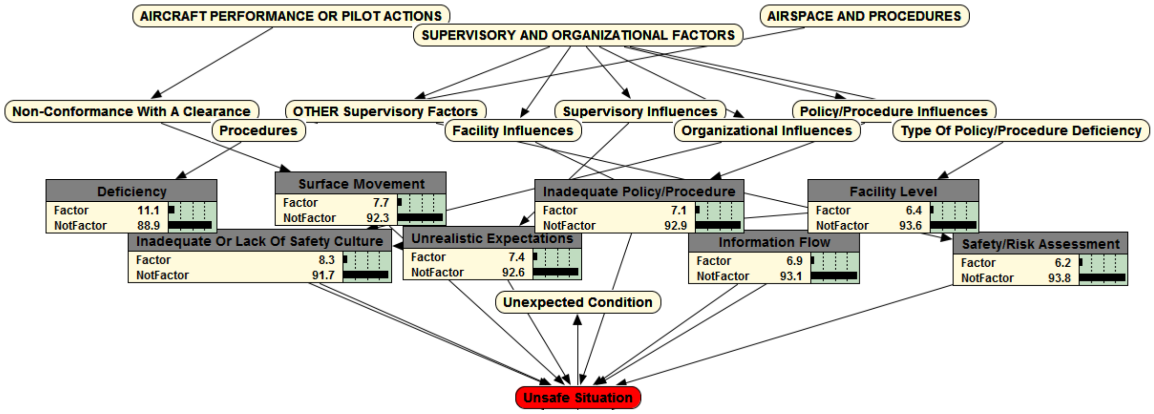


Figure 38: Unsafe Situation Probabilistic Network

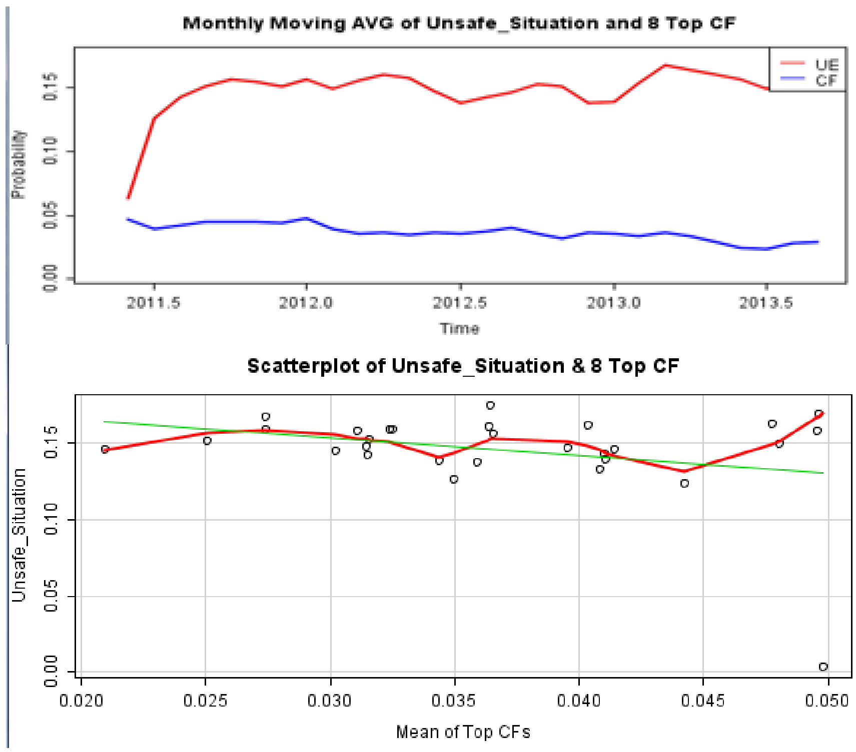


Figure 39: Unsafe Situation & Top Causal Factors Correlation

4.2.4. Altitude

Altitude events are incidents that are safety risks or violations related to some kind of altitude-related situations, such as separation, communication, coordination, performance etc. As shown in the table 6, most of the 7 top causal factors identified in the model are directly related to altitude problem involving clearance, readback, and information exchange issues. The structure of the network indicates that there is a correlation between two causal factors, “altitude non-conformance with a clearance” and “altitude readback problem” which is somehow intuitive. If there is a readback problem, it is likely that there is a communication problem and as a result the operating crew will fail to confirm to the altitude clearance. The time series plots show that there is some consistency in the relationship between the aggregate of the top causal factors and the event frequency except for the time period between early 2012 and mid-2012 when there was a larger spike in the frequency of the event. The scatterplot confirms this correlation.

Table 6: Altitude Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Non-Conformance with a Clearance/Altitude	A pilot/aircrew incorrectly executes the provisions of an altitude clearance	0.056	0.277
2	Clearance Problem/Altitude	Issuing instruction other than what was authorized or intended	0.176	0.294
3	Readback Problem/Altitude	Altitude assignment was made properly, but the individual did not read it back accurately	0.043	0.161
4	Aircraft Performance or Pilot Response/Timely Aircraft Descent or Climb	The combined performance of the aircrew and the aircraft capability results in an untimely descent/climb	0.077	0.162

5	Information Exchange/Flight Level	Intra/inter facility exchange of information involving flight level, or lack thereof, between controllers	0.058	0.137
6	Non-Conformance with a Clearance/Altitude Crossing	A pilot/aircrew incorrectly executes the provisions of a crossing requirement	0.012	0.054
7	Aircraft Acknowledgement/Wrong Aircraft Acknowledged	Transfer of information related to the movement of aircraft or the use of airspace wrongly received	0.033	0.071

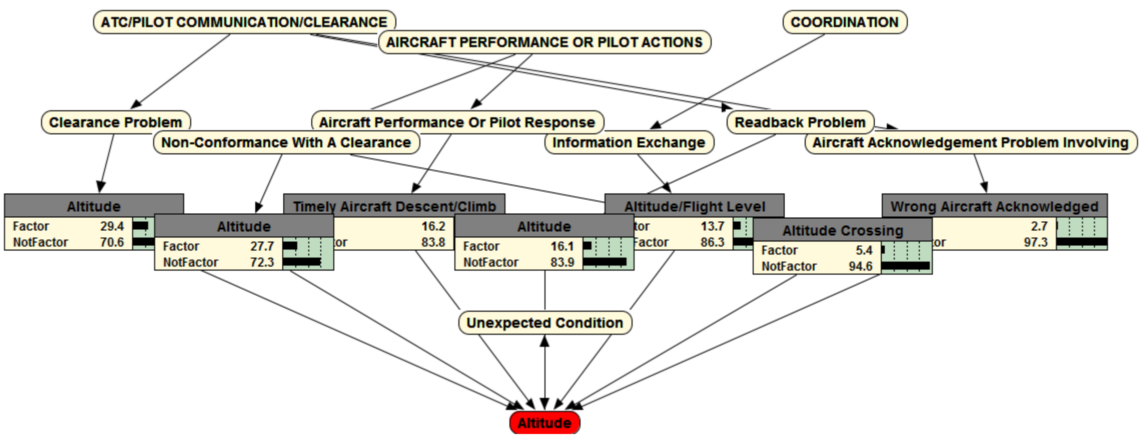


Figure 40: Altitude Probabilistic Network

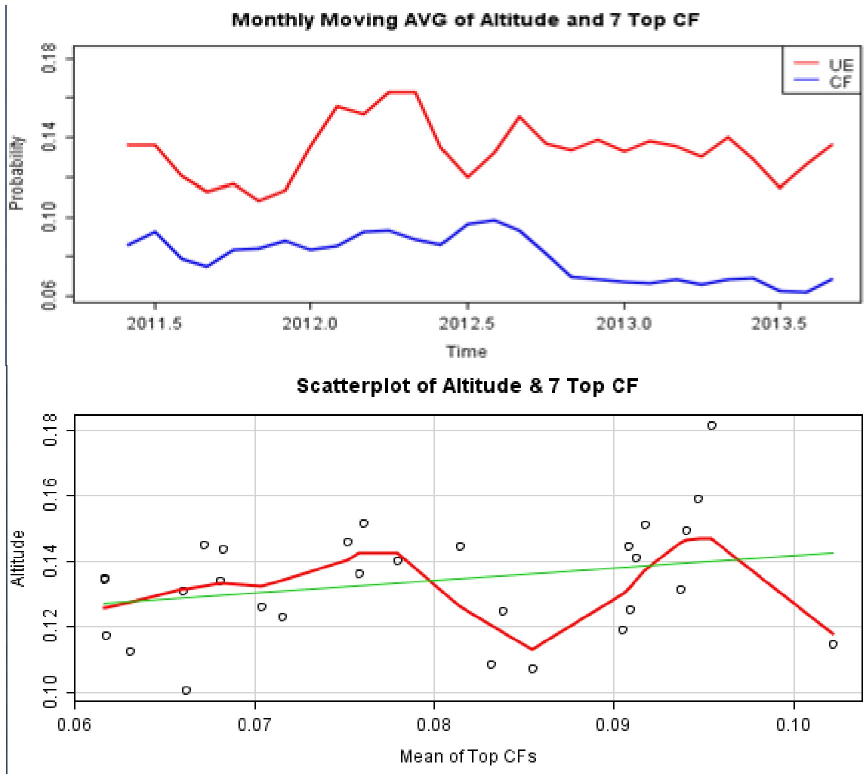


Figure 41: Altitude & Top Causal Factors Correlation

4.2.5. Course/Routing

Course/Routing events are non-separation issues that are related to course and usually happen during the routing of aircraft. As shown in table-7, most of course/routing events occur due to 6 causal factors involving clearance problems, data processing, information exchange, and aircraft performance. The structure of the model shows that there exist stronger correlations between "clearing routing" and "flight plan", and "heading clearance" and "flight plan" causal factors. The monthly moving average time series plots show that a relatively stronger relationship exists between the aggregate of the six top causal factors and the event frequency. The scatterplot shows a similar stronger relationship between the two.

Table 7: Course/Routing Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Non-Conformance with a Clearance/Course	A pilot/aircrew incorrectly executes the provisions of a heading/route/course assignment	0.058	0.254
2	Clearance Problem/Cleared Routing	Issuing a routing other than what was authorized or intended	0.048	0.157
3	Flight Data Processing/Flight Plan	Errors in understanding and processing flight plan information	0.022	0.119
4	Information Exchange/Route of Flight	Intra/inter facility exchange of information involving route of flight, or lack thereof, between controllers	0.039	0.109
5	Clearance Problem/Heading	Issuing a heading instruction other than what was authorized or intended	0.08	0.13
6	Aircraft Performance or Pilot Response/Timely Aircraft Turn	The combined performance of the aircrew and the aircraft capability results in an untimely turn	0.059	0.109

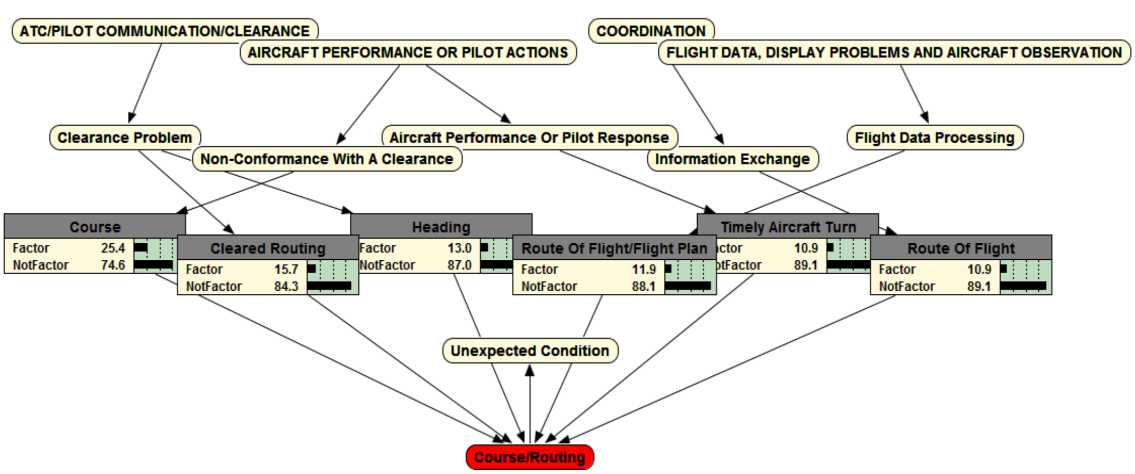


Figure 42: Course/Routing Probabilistic Network

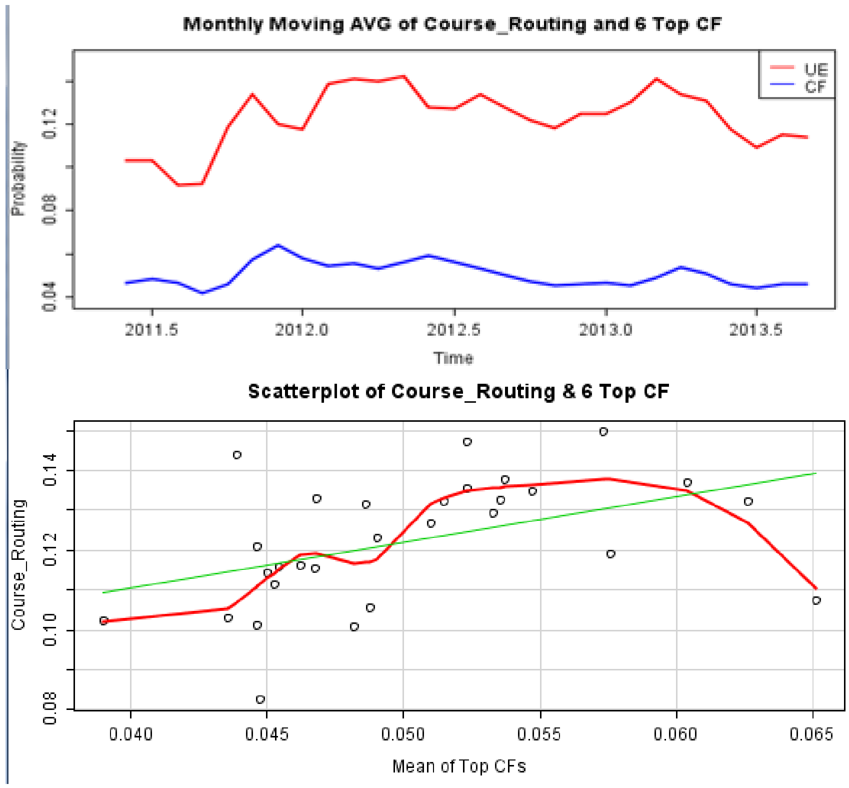


Figure 43: Course/Routing & Top Causal Factors Correlation

4.2.6. Runway Incursion

Runway Incursions are separation events that occur at airport facilities (runway or taxiway area) and occasionally present collision risks. They happen when either two or more aircraft, or aircraft and other vehicles get close together below the standard separation distance. Most of the 6 top causal factors identified by the model (see table-8) are related to clearance problems and coordination issues during takeoff, landing, and ground movement. The model structure shows a correlation between two pairs of causal factors, “take-off clearance problem” with “non-conformance clearance problem involving surface movement” and “hold short clearance problem” with “crossing active runway coordination problem”. The moving average time series plots show a consistent and relatively stronger relationship between the top causal factors and the event frequency. Also, the continuous decline in the frequency of runway incursions in the past two years is independently confirmed with the yearly reports published by the runway safety office of the FAA. The stronger correlation between the aggregate top causal factors and the event frequency is also shown in the scatterplot.

Table 8: Runway Incursion Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Non-Conformance with a Clearance/Surface Movement	A pilot/aircrew incorrectly executes the provisions of a taxi instruction	0.037	0.309
2	Clearance Problem/Take-off	Issuing a take-off clearance other than what was authorized or intended	0.035	0.134
3	Coordination Ground & Local/Crossing Active Runway	Crossing of active runway as a result of inadequate exchange of information between ground and local	0.011	0.107
4	Clearance Problem/Landing Clearance	Issuing a landing clearance other than what was authorized or intended	0.015	0.101
5	Clearance Problem/Hold Short	Issuing an incomplete or incorrect hold short instruction	0.009	0.091
6	Aircraft Performance or Pilot Action/Timely Runway Exit	The combined performance of the aircrew and the aircraft capability results in an untimely runway exit	0.012	0.09

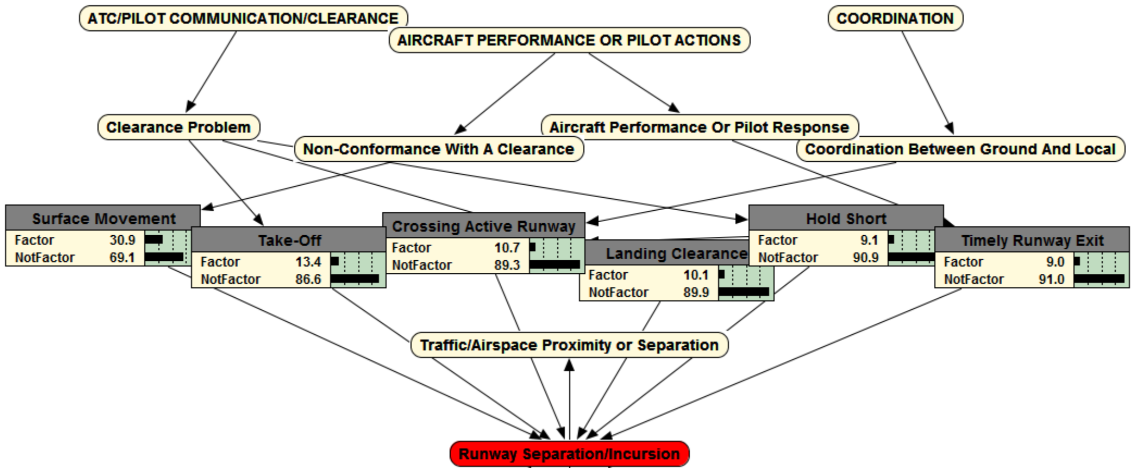


Figure 44: Runway Incursion Probabilistic Network

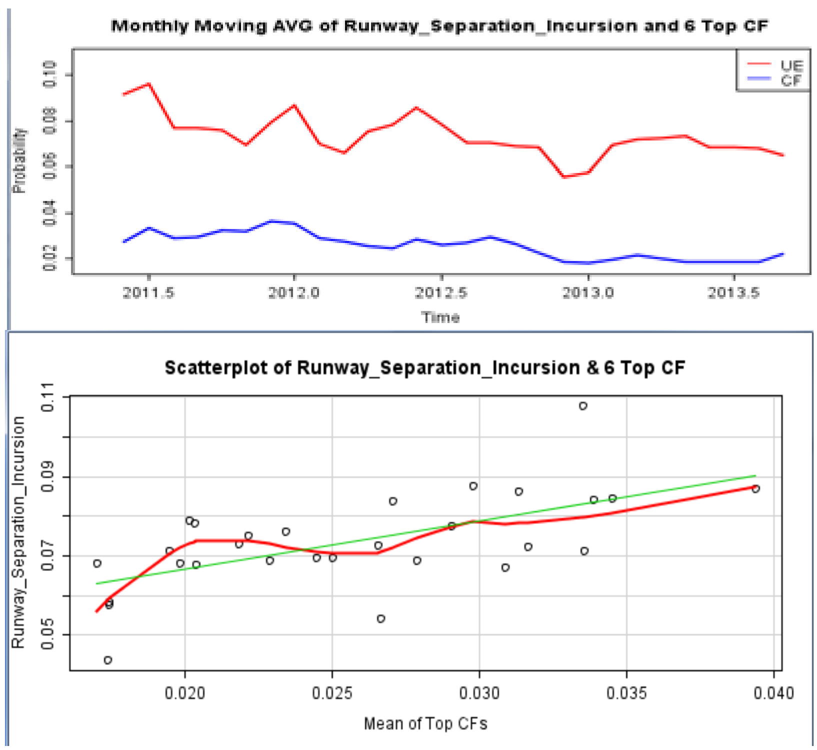


Figure 45: Runway Incursion & Top Causal Factors Correlation

4.2.7. TCAS-RA/Evasive Action

TCAS-RA is a type of separation event that requires evasive action as a response to a Resolution Advisory (RA) initiated from Traffic Collision Avoidance System (TCAS) that ultimately conflicts with another aircraft. The 8 significant causal factors for evasive actions, shown in table-9, involve issues such as clearance, aircraft performance, airspace design, and special events. The structure of the network identifies the correlation between causal factors such as "altitude clearance" with "visual separation clearance" and "airspace complexity" with "open skies/photo missions". The time series plots indicate the consistent and stronger relationship between the aggregate of the top causal factors and the event frequency except for the time period around the beginning of 2012. The scatterplot also shows a relatively stronger correlation between the factors and the event.

Table 9: TCAS-RA Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Clearance Problem/Altitude	Issuing instruction other than what was authorized or intended	0.176	0.249
2	Aircraft Performance or Pilot Response/Timely Aircraft Descent or Climb	The combined performance of the aircrew and the aircraft capability results in an untimely descent/climb	0.077	0.127
3	Non-Conformance with a Clearance/Altitude	A pilot/aircrew incorrectly executes the provisions of a crossing requirement	0.06	0.101
4	Aircraft Performance or Pilot Response/Timely Aircraft Turn	The combined performance of the aircrew and the aircraft capability results in an untimely turn	0.059	0.099
5	Clearance Problem/Visual Separation	Issuing an incomplete or incorrect visual clearance	0.027	0.067

6	Outside Influences/Airspace Complexity	Airspace configuration (changing/abnormal) creates undue stress to an individual	0.049	0.085
7	Airspace Design/Poor or Outdated Design	Poor or outdated airspace design which contributes to undesired outcome	0.015	0.047
8	Special Event/Open Skies or Photo Missions	The operations required by observation flights	0.006	0.031

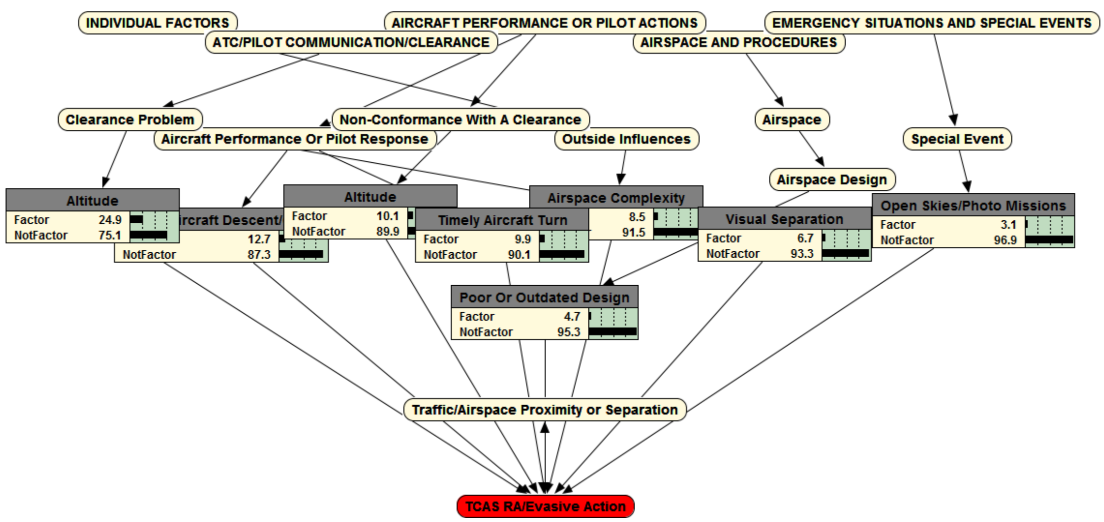


Figure 46: TCAS-RA Probabilistic Network

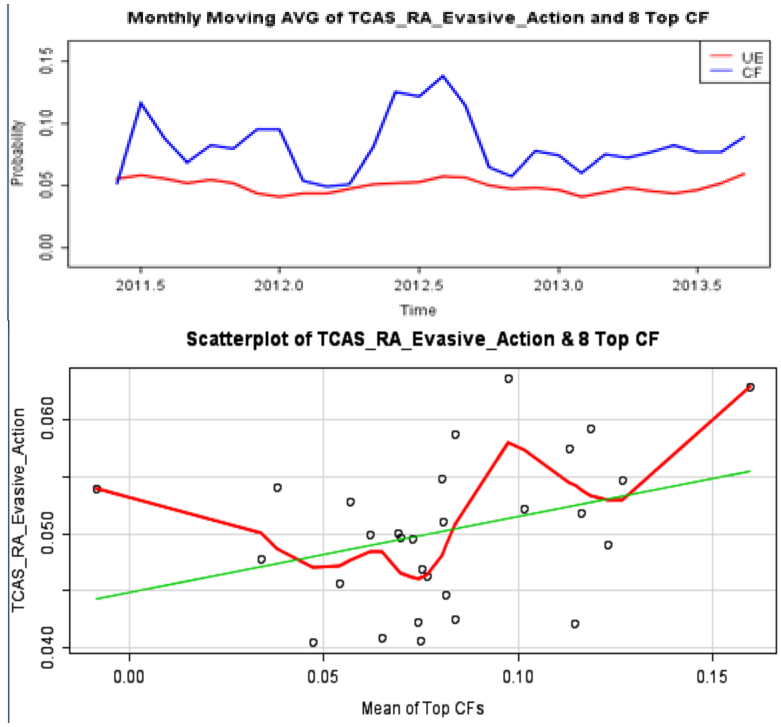


Figure 47: TCAS-RA & Top Causal Factors Correlation

4.2.8. VFR to IFR

VFR (Visual Flight Rules) to IFR (Instrument Flight Rules) events are loss of separation incidents that involve a mix of VFR and IFR flights. In VFR, flights are conducted using low-altitude navigation with visual reference to the ground and conflicts are avoided visually. As shown in table-10, the 8 significant causal and/or contributing factors for VFR to IFR separation problems include issues such as special events, aircraft performance, individual factors, and airspace designs. The structure of the probabilistic network shows correlations between two pairs of the top causal factors, "lack of planning with other controllers" with "open skies/photo missions" and "visual separation" with "untimely transfer of communication". The time series plots show a non-varying event frequency and consistently changing aggregate of the top causal factors and yet the two are related. The same fact is displayed in the scatterplot although the correlation is not particularly strong.

Table 10: VFR to IFR Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Special Event/Open Skies or Photo Missions	The operations required by observation flights	0.006	0.052
2	Special Event/Skydiving, Balloon, Glider Activity	Special event involving skydiving, balloon, glider activity	0.004	0.04
3	Aircraft Performance/Military Activity	Military operations that cause and or contribute to an undesired outcome	0.027	0.059
4	Clearance Problem/Visual Separation	Issuing an incomplete or incorrect visual clearance	0.027	0.058
5	Controller Actions/Inadequate Plan of Action Developed	Risk was not recognized or misjudged and the devised action or plan by the individual is inadequate for the situation	0.134	0.161
6	Controller Influences/Lack of Planning with Other Controllers	A lack of planning and coordination with others	0.066	0.088
7	Airspace Design/Poor or Outdated Design	Poor or outdated airspace design which contributes to undesired outcome	0.015	0.042
8	Clearance Problem/Untimely Transfer of Communication	Not issuing a frequency change as coordinated	0.022	0.049

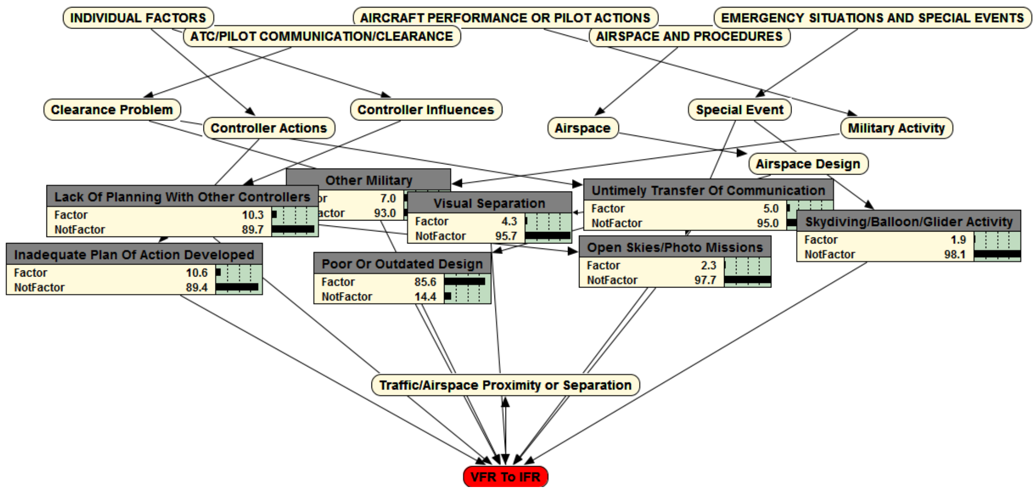


Figure 48: VFR to IFR Probabilistic Network

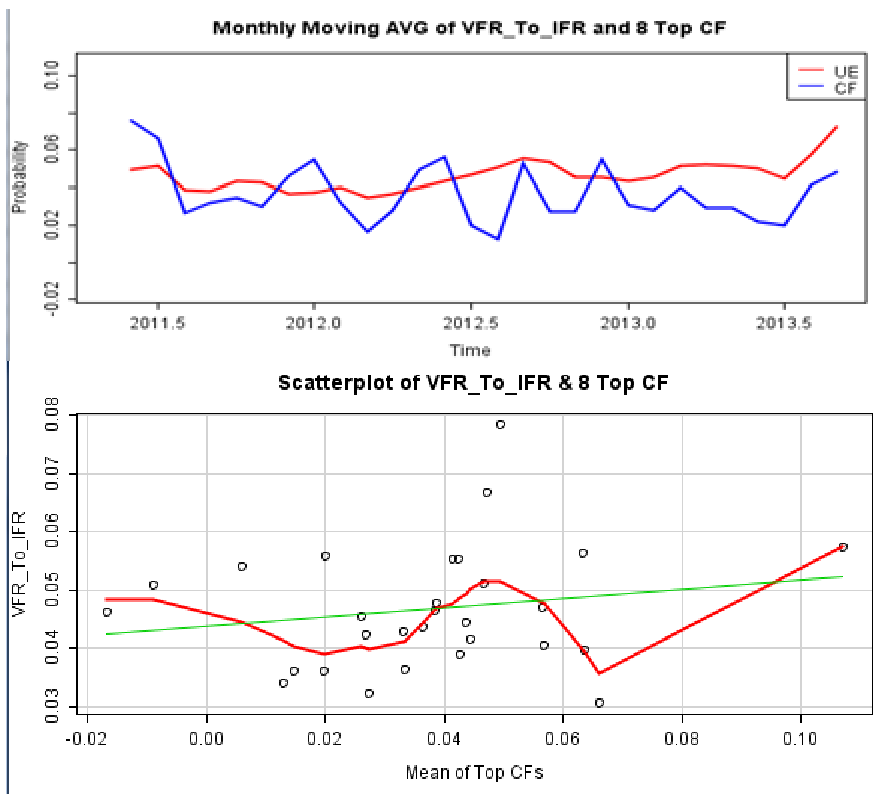


Figure 49: VFR to IFR & Top Causal Factors Correlation

4.2.9. Go Around

Go Around is a procedure or flight maneuver done during the landing phase in which the landing procedure is discontinued for another try. Although occasionally it becomes necessary to do go around procedure for various reasons, it is usually a result of some safety related causes and carries a risk as it involves a sudden change of the phase of flight. The 7 significant ATC-related causal and/or contributing factors identified by the model for go around incidents are related to aircraft performance issues and clearance problems, both of which are frequently happening phenomena around airports. However, unlike most of the event models shown in this research, the top causal factors for go around vary drastically. The time series plots indicate that the only period that this set of causal factors were consistently the primary issues were between mid-2011 and early 2012. The two plots show a surprisingly fluctuating relationship throughout the rest of the time periods shown in the plots. This needs further research to identify why the causal factors vary so often. One approach would be to build models for individual airports to identify causal and contributing factors that maybe localized in nature (see section 4.3). As a result of these variations, the scatterplot shows no meaningful correlation between the aggregate of the top causal factors and go around event. The probabilistic network structure shows that three pairs of correlations between the causal factors given the structure, "clearance non-conformance" with "timely runway exit", "timely roll" with "landing clearance", and "clearance non-conformance" with "timely speed adjustment".

Table 11: Go Around Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Aircraft Performance or Pilot Response/Compression on Final	Different aircraft categories and their aerodynamic configuration causes a speed difference on final approach	0.048	0.216
2	Aircraft Performance or Pilot Action/Timely Runway Exit	The combined performance of the aircrew and the aircraft capability results in an untimely runway exit	0.019	0.161
3	Non-Conformance with a Clearance/Surface Movement	A pilot/aircrew incorrectly executes the provisions of a taxi instruction	0.033	0.14
4	Aircraft Performance or Pilot Response/Timely Roll	The combined performance of the aircrew and the aircraft capability results in an untimely departure roll	0.014	0.108
5	Clearance Problem/Landing Clearance	Issuing a landing clearance other than what was authorized or intended	0.015	0.081
6	Aircraft Performance or Pilot Response/Timely Speed Adjustment	The combined performance of the aircrew and the aircraft capability results in an untimely speed adjustment	0.035	0.098
7	Clearance Problem/Approach Clearance	Issuing an approach clearance other than what was authorized or intended	0.033	0.074

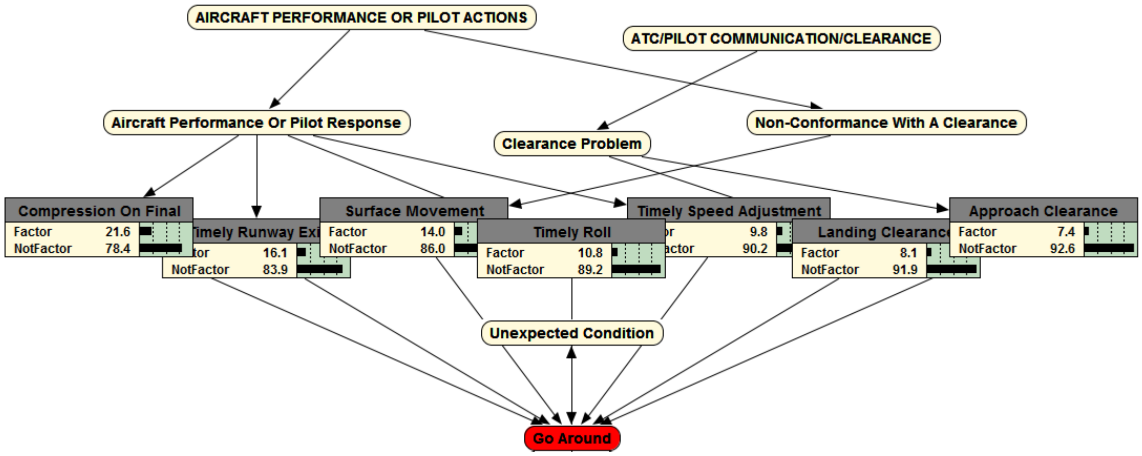


Figure 50: Go Around Probabilistic Network

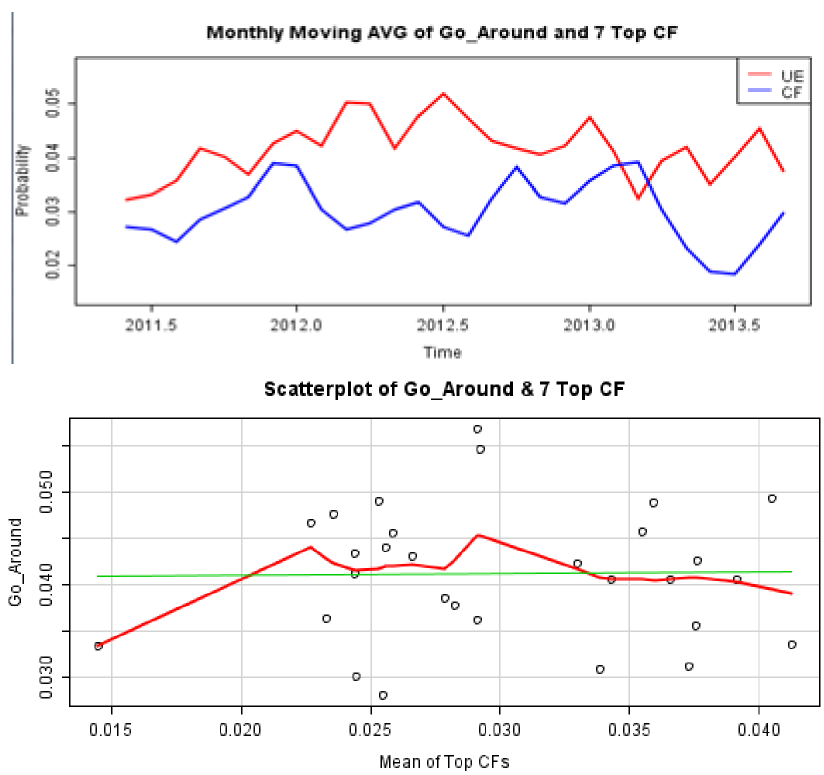


Figure 51: Go Around & Top Causal Factors Correlation

4.2.10. Wake Turbulence

Wake turbulence events are caused by the turbulence effects of one aircraft on other aircraft nearby, usually behind, but also on those on parallel paths primarily during landing and takeoff phases. The turbulence is created by the spillover of the air at the wingtip due to the pressure differential between the lower and upper surface of the wing. Depending on the strength of the turbulence, the separation distance, and size of the affected aircraft, wake turbulence can lead to issues that range from minor instability to a major aircraft roll. The 6 significant causal factors (see table-12) for turbulence incidents identified in the model include issues like aircraft performance, pilot response, and clearance problems. Pilot response is one of the top factors mainly because flight crews are primarily responsible to operate aircraft in the optimal path for wake turbulence with little assistance from ATC within the given clearance. The structure of the causal model shows no correlation between any pair of the causal factors given the learned structure, which implies that all the causal factors are independent of each other for wake turbulence events. However, the time series plots and the scatterplot display a relatively strong relationship between the aggregate of the top causal factors and wake turbulence event frequency. Similarly, the strong correlation between the two parameters is shown in the scatterplots.

Table 12: Wake Turbulence Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Aircraft Performance or Pilot Response/Compression on Final	Different aircraft categories and their aerodynamic configuration causes a speed difference on final approach	0.048	0.29

2	Aircraft Performance/Heavy Jet	Aircraft capable of takeoff weights of 300,000 pounds or more whether or not they are operating at this weight during a particular phase of flight	0.019	0.215
3	Clearance Problem/Take-Off	Issuing a take-off clearance other than what was authorized or intended	0.035	0.122
4	Aircraft Performance or Pilot Response/Timely Speed Adjustment	The combined performance of the aircrew and the aircraft capability results in an untimely speed adjustment	0.035	0.101
5	Clearance Problem/Visual Separation	Issuing an incomplete or incorrect visual clearance	0.027	0.092
6	Clearance Problem/Speed	Issuing a speed instruction other than what was authorized or intended	0.027	0.085

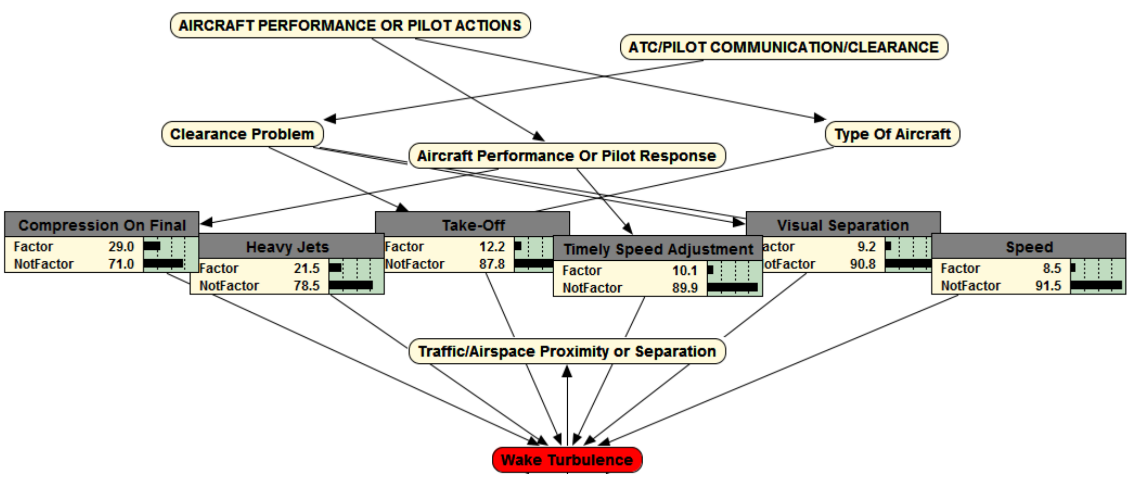


Figure 52: Wake Turbulence Probabilistic Network

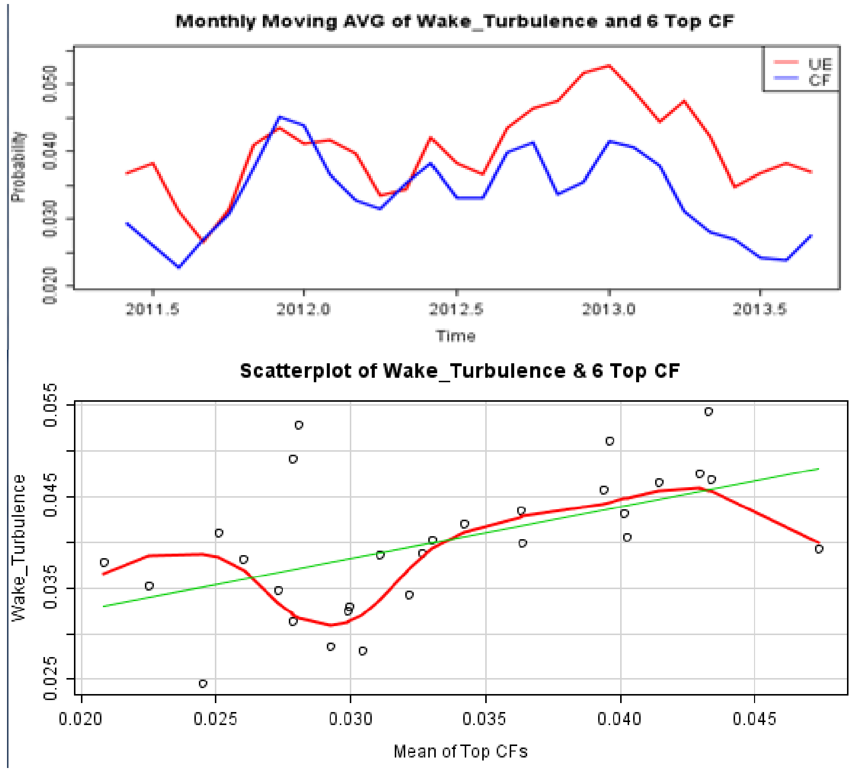


Figure 53: Wake Turbulence & Top Causal Factors Correlation

4.2.11. Terrain/Obstruction

Terrain or Obstruction event happens when a separation is lost due to proximity to terrain or other obstructions in the flight path. There are 8 significant factors identified (table-13) in the model, and much like separation issues that involve multiple aircraft, terrain or obstruction separation problems are primarily caused by factors such as clearance problems and aircraft performance issues. In addition, factors related to safety alert equipment play a role in causing obstruction incidents. As shown in the time series plots, no consistent relationship exists between the aggregate of the top causal factors and obstruction events as a result of the frequent changes in the causal factors without a corresponding change in the event frequency. Due to such discrepancy, no correlation is indicated on the scatterplots. However, the structure of the network indicates that there are correlations between two pairs of causal factors, "LA/MSAW" with "false alert" and "altitude clearance" with "altitude readback problems".

Table 13: Terrain/Obstruction Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Clearance Problem/Altitude	Issuing instruction other than what was authorized or intended	0.176	0.382
2	Clearance Problem/Heading	Issuing a heading instruction other than what was authorized or intended	0.08	0.188
3	Non-Conformance with a Clearance/Altitude	A pilot/aircrew incorrectly executes the provisions of a crossing requirement	0.056	0.175
4	Non-Conformance with a Clearance/Course	A pilot/aircrew incorrectly executes the provisions of a heading/route/course assignment	0.058	0.161
5	Aircraft Performance or Pilot Response/Timely Aircraft Descent or Climb	The combined performance of the aircrew and the aircraft capability results in an untimely descent/climb	0.071	0.146
6	Readback Problem/Altitude	Altitude assignment was made properly, but the individual did not read it back accurately	0.043	0.122
7	Safety Alert Equipment/LA (MSAW)	The functions that aid the controller by alerting when a tracked aircraft is below or predicted by the computer to go below the predetermined altitude	0.002	0.041
8	Safety Alert Malfunction/False Alert	An alert generated by one or more false targets that the system has interpreted as real tracks and placed into safety logic	0.005	0.028

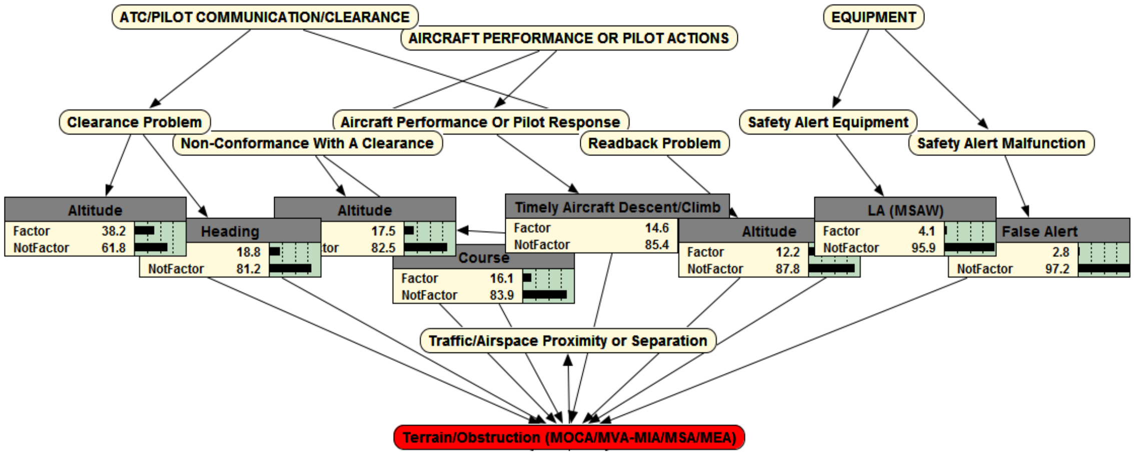


Figure 54: Terrain/Obstruction Probabilistic Network

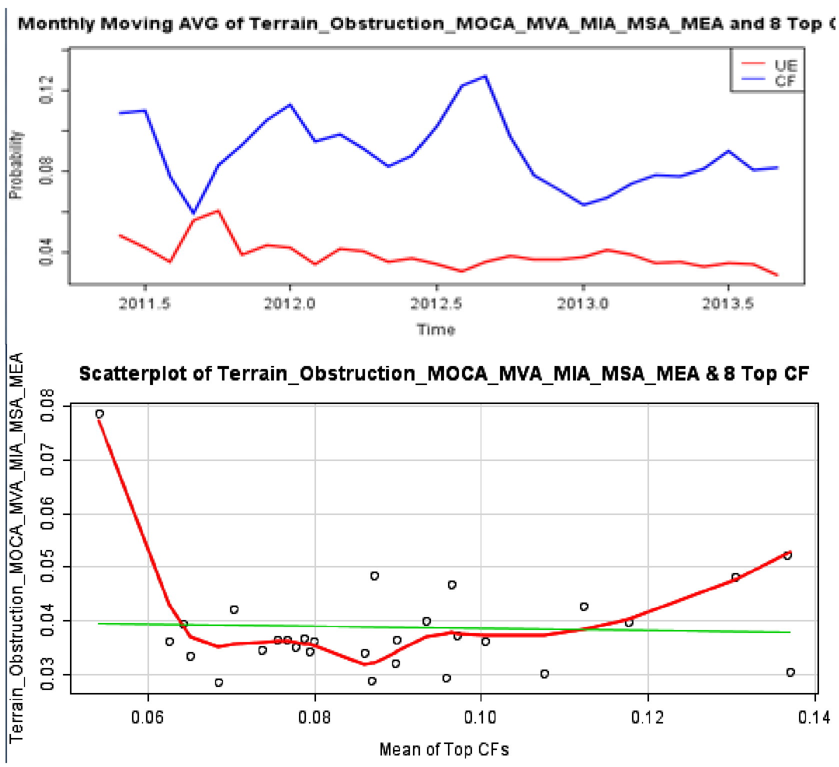


Figure 55: Terrain/Obstruction & Top Causal Factors Correlation

4.2.12. Speed

Speed events are unexpected condition incidents that are related to speed issues resulting in undesired outcome. Speed events may lead to a loss of standard separation. The fact that 3 of the 7 significant causal factors are issues primarily related to aircraft performance should be of no surprise. Speed issues are related more to aircraft performance and pilot actions more than any other variables. However, speed clearance problems and information exchange issues are also contributing factors for speed events. Given the learned structure of the network, “timely speed adjustment” and “compression on final” are correlated. Although not as strong as shown on some of the other event models, there is a relationship between the aggregate top causal factors and the event frequency. One can see an interesting phenomenon shown on the time series plots around mid-2012, the relative frequency of speed issues went down while the top causal factors are actually increased. This has contributed to the relatively weaker correlation between the aggregate factors and the event as shown in the scatterplot.

Table 14: Speed Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Aircraft Performance or Pilot Response/Timely Speed Adjustment	The combined performance of the aircrew and the aircraft capability results in an untimely speed adjustment	0.035	0.306
2	Aircraft Performance or Pilot Response/Compression on Final	Different aircraft categories and their aerodynamic configuration causes a speed difference on final approach	0.048	0.256
3	Clearance Problem/Speed	Issuing a speed instruction other than what was authorized or intended	0.027	0.17

4	Information Exchange/Speeds	Intra/inter facility exchange of information involving speeds, or lack thereof, between controllers	0.01	0.087
5	Non-Conformance with a Clearance/Speed	A pilot/aircrew incorrectly executes the provisions of a speed assignment	0.006	0.075
6	Controller Actions/Action or Plan Execution	Execution of a particular action and/or plan is poor/inadequate for the situation	0.183	0.232
7	Aircraft Performance/Heavy Jet	Aircraft capable of takeoff weights of 300,000 pounds or more whether or not they are operating at this weight during a particular phase of flight	0.019	0.047

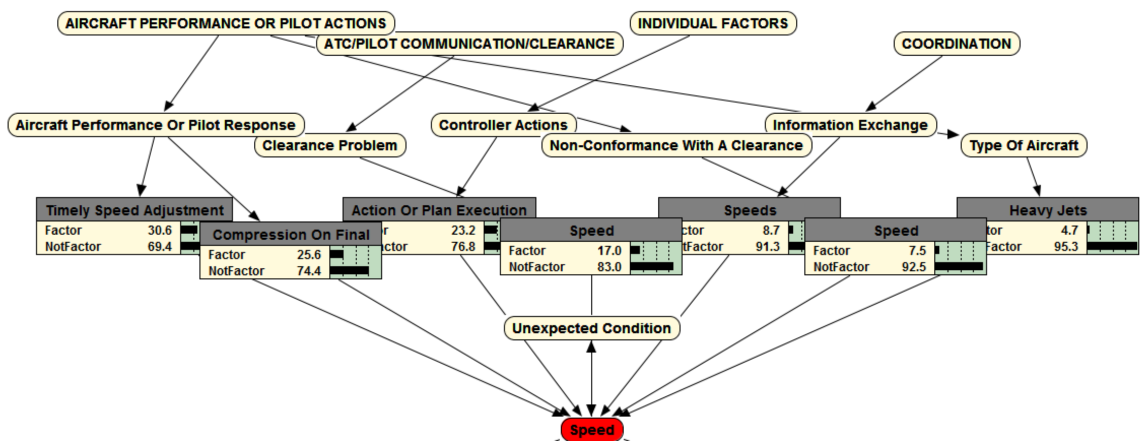


Figure 56: Speed Probabilistic Network

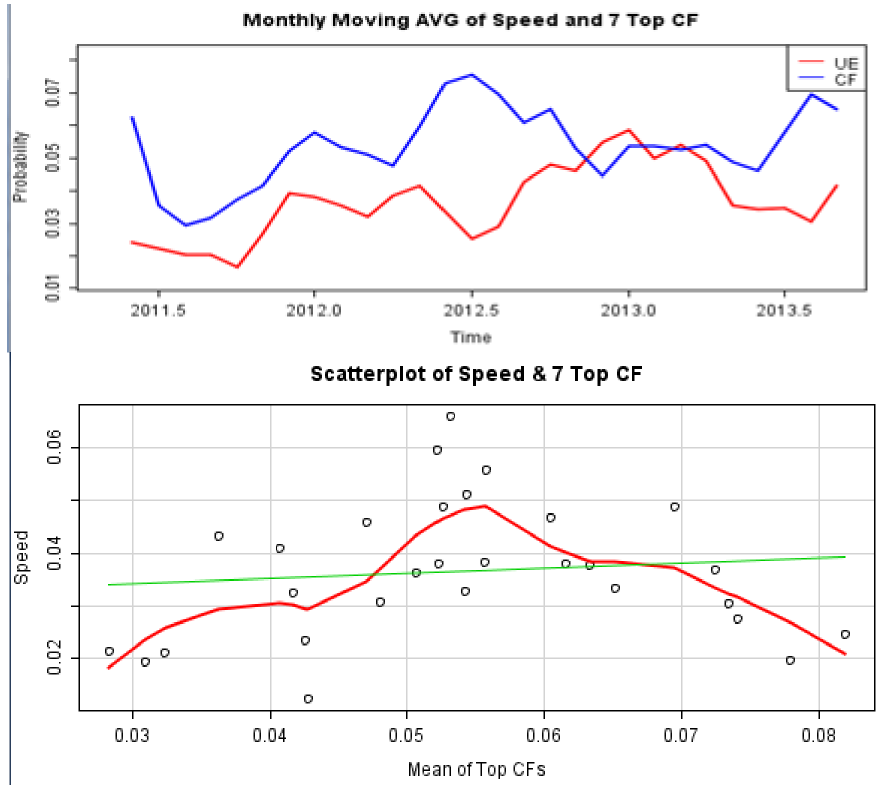


Figure 57: Speed & Top Causal Factors Correlation

4.2.13. Equipment

Equipment related events are those incidents that are caused by ATC-related hardware or software problems, but not equipment that are related to aircraft systems. By far the top issue is ERAM, it is a newly implemented automation software system to process flight radar data and generate display information for controllers at facilities that handle high-altitude traffic. ERAM's multifaceted problems are well documented in audit reports by Office of Inspector General in 2012 and 2013. Not surprisingly all of the other causal and/or contributory factors of equipment-caused events are the result of malfunctioning and deficiency of hardware or software components, (see table-15). The structure of the model identifies correlation between "radar malfunction" and "false alert". The relationship between the aggregate of the top causal factors and equipment issues are particularly strong and consistent throughout the time period modeled. The scatterplot shows such a strong correlation as well.

Table 15: Equipment Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Equipment Automation/ERAM	En Route Automation Modernization	0.014	0.191
2	Equipment/Malfunction	The breakdown, or failure of equipment that is not communication, navigation or surveillance based	0.008	0.126
3	Equipment/Radar or Surveillance Equipment Malfunction	The unexpected breakdown or failure of equipment used to track aircraft	0.006	0.106
4	Equipment/Radar or Surveillance Equipment Outage	The scheduled shutdown or scheduled maintenance of equipment used to track aircraft	0.006	0.069
5	Equipment/Radar or Surveillance Equipment/Coverage	Issues with the coverage of equipment used to track aircraft	0.01	0.064
6	Safety Alert Malfunction/False Alert	An alert generated by one or more false targets that the system has interpreted as real tracks and placed into safety logic	0.005	0.054
7	Work Area Influences/Software Design Issue	The software in the immediate work environment requires procedures that cause an undesirable outcome	0.008	0.053
8	Work Area Influences/Equipment Design Issue	The equipment in the immediate work environment requires procedures that cause an undesirable outcome	0.007	0.042

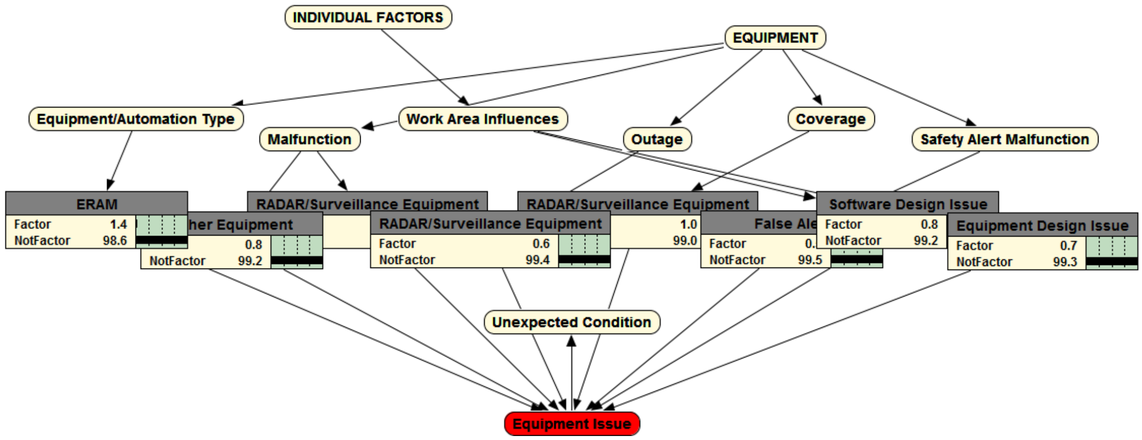


Figure 58: Equipment Probabilistic Network

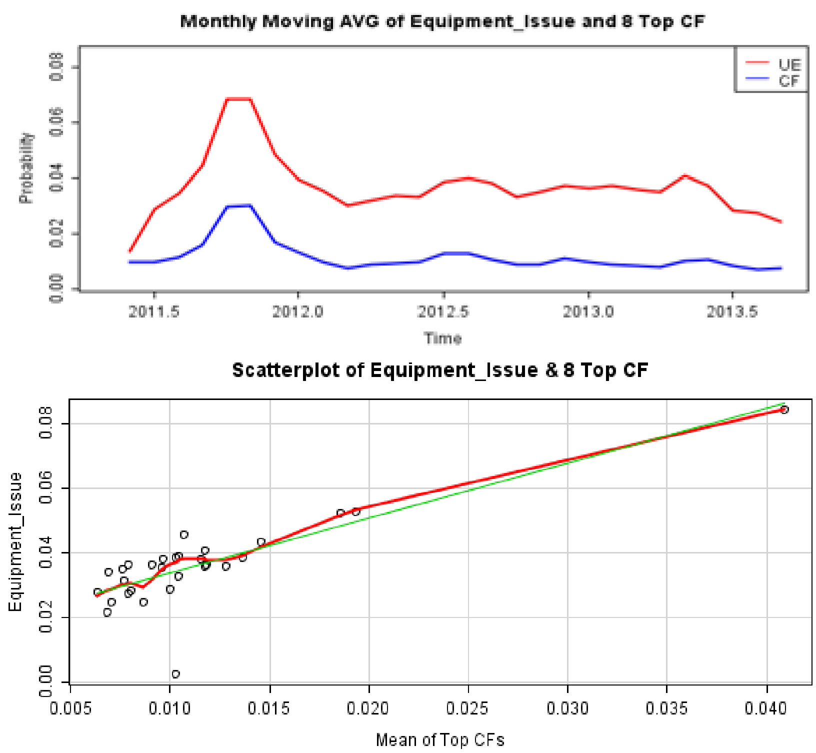


Figure 59: Equipment & Top Causal Factors Correlation

4.2.14. Aircraft Emergency

Aircraft emergency events are incidents which are usually caused by a large scale deviation from normal operations which require urgency. These are events related to non-routine system degradation, equipment malfunction, operator incapacitation, or environmental circumstances. Most of the 6 top factors identified by the causal model (see table-16) are not the usual kind of causal factors that are likely to lead to emergency events; they are instead elaboration of the state of the emergency and its initiation. For instance, the fact that an emergency was declared by a pilot or a controller is not really a causal factor, but tells us about who requested the emergency procedure. As a result, there will always be a strong relationship between such factors and the event which is shown in the time series plots and scatterplot. In addition, a correlation between "pilot-declared events" and "IMC condition" is identified in the structure of the learned network.

Table 16: Aircraft Emergency Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Emergency Situation/Pilot Declared	A distress or urgency condition causing a pilot to declare emergency	0.011	0.491
2	Emergency Situation/Emergency Landing	A distress or urgency condition causing an emergency landing	0.016	0.288
3	Emergency Situation/Expedited Handling	An aircraft in distress which is afforded priority over other aircraft causing undesired outcome	0.007	0.278
4	Emergency Situation/Controller Declared	A distress or urgency condition causing a controller to declare emergency	0.003	0.147

5	Meteorological Conditions/IMC	Instrument meteorological conditions expressed in terms of visibility, distance from cloud, and ceiling less than the minima specified	0.02	0.046
6	Information Exchange/Special Instructions	Intra/inter facility exchange of information involving special instruction, or lack thereof, between controllers	0.055	0.063

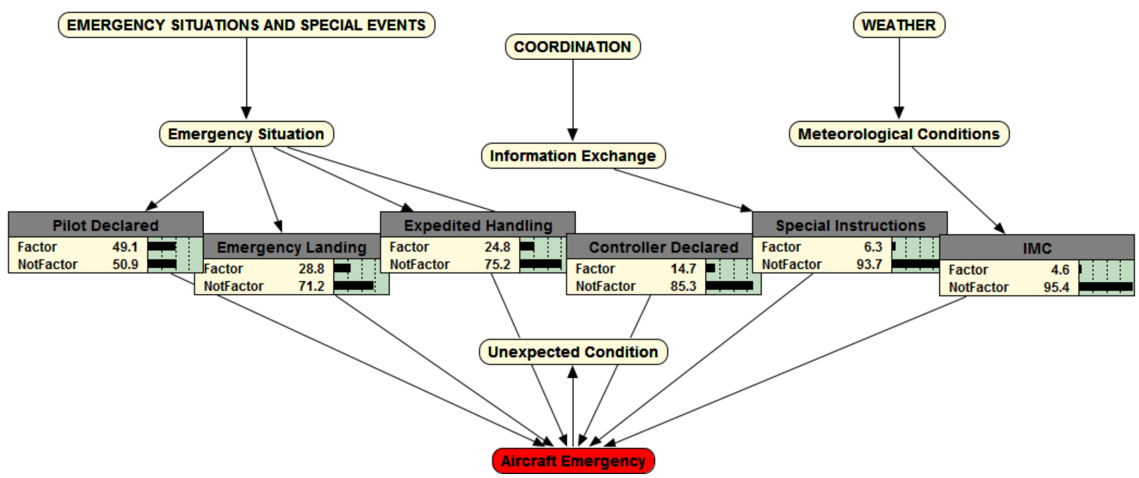


Figure 60: Aircraft Emergency Probabilistic Network

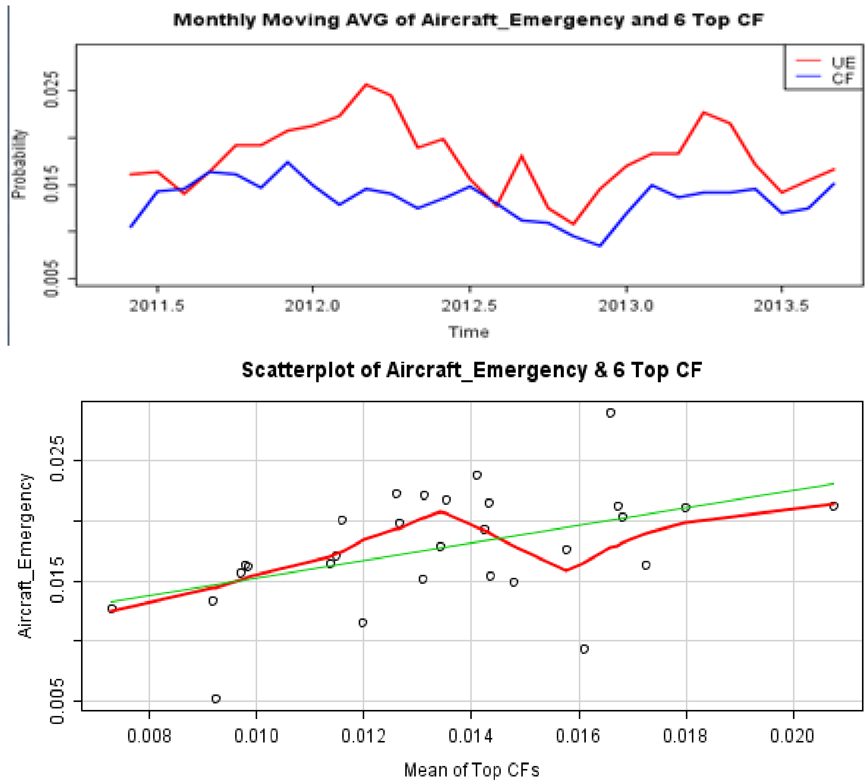


Figure 61: Aircraft Emergency & Top Causal Factors Correlation

4.2.15. NORDO

NORDO, also known as NORAC, events are incidents that are caused by loss of radio communication when it is required that radio communication is established. Most of the 6 significant causal factors for NORDO/NORAC events are related to radio frequency issues and communication problems (see table-17). The aggregate of the top causal factors have strong relationship with the event frequency throughout the two years period implying that the same set of contributing factors has been the primary source of NORDO events. Such correlation is also shown on the scatterplot. Given the learned structure on the network, "aircraft on incorrect frequency" factor is related to "lose of communication" issue.

Table 17: NORDO Top Causal Factors

Rank	Causal Factor	Description	Prior	Posterior
1	Loss of Communication/Aircraft on Incorrect Frequency	Aircrew being on an incorrect frequency	0.019	0.352
2	Aircraft Acknowledgement Problem/Acknowledgement not Received	Transfer of information related to the movement of aircraft or the use of airspace not received	0.025	0.167
3	Loss of Communication/Poor Coverage or Interference	Unable to maintain communications due to limitations of airborne radio signals	0.008	0.146
4	Loss of Communication/Other Communication Issue	Aircraft operating in the NAS without radio communications	0.029	0.158
5	Clearance Problem/Untimely Transfer of Communication	Not issuing a frequency change as coordinated	0.022	0.084
6	Information Exchange/Special Instructions	Intra/inter facility exchange of information involving special instruction, or lack thereof, between controllers	0.055	0.104

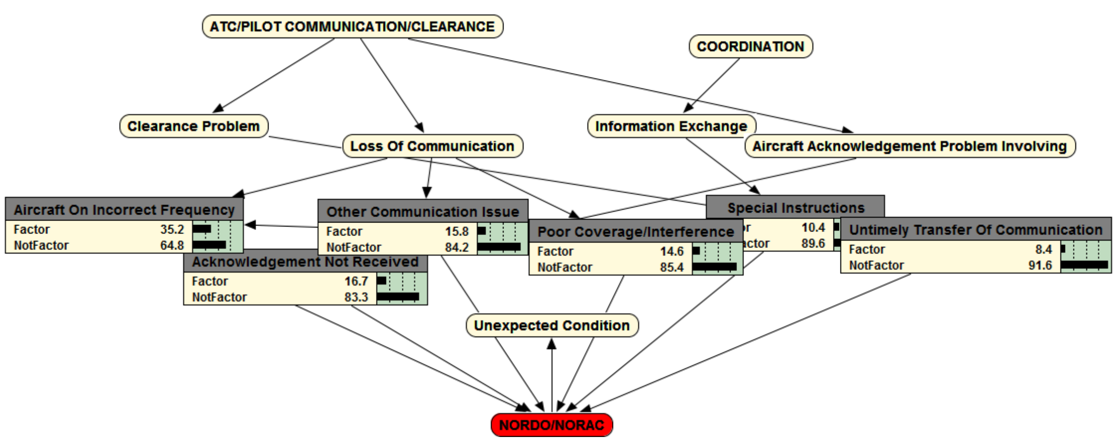


Figure 62: NORDO Probabilistic Network

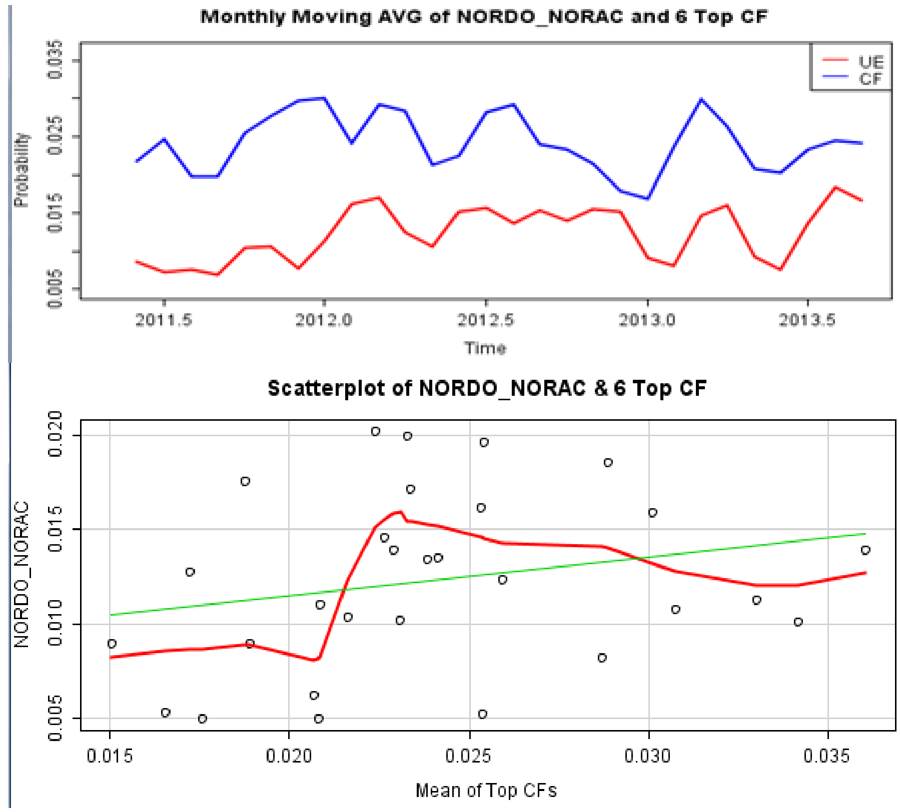


Figure 63: NORDO & Top Causal Factors Correlation

4.3. Variations in Relationships of Factors

The relationship between the aggregate causal factors and event frequency on some events, such as IFR to IFR, Unsafe Situation, Terrain, and Go Around, vary significantly. There could be a number of reasons for such variations as there are many factors responsible for changes in the NAS over time. One potential area for further analysis to identify the root cause of such discrepancy is the difference between local-specific and nation-wide factors. All the models created in this research are based on NAS-wide data although some factors are better explained by the unique situations of the particular ATC facilities that are involved in the incidents. As a result, part of the sudden changes in the relationships can be analyzed by isolating the data points for specific facilities or facility types and build models independently. One obvious challenge for such approach is that it causes data fragmentation, and for small facilities there just may not be enough records. Another method to determine the cause for relationships variation is to separately analyze the dataset in the time regions where the variations occur. In the regions where the variation is high, the significant causal factor for the overall regions don't hold, which means other factors are also in play for various reason that can only be fully answered with an independent research.

Of the four significant causal factor models explained in section 4.2, Go Around has the highest variation in short time intervals, which resulted in significant causal factors with a weak relationship with the event. Such drastic variations of relationships cannot be analyzed by using separate models since there is a high frequency change that would cause excessive fragmentation of the dataset. So, dividing the dataset by facility is a better and simpler approach to study the variations in Go Around event factors relationships.

In ATSAP dataset, the facility with relatively higher proportion of Go around is San Francisco International airport (SFO). The average proportion of Go around in SFO is 24% whereas the overall proportion in the NAS is just over 4%. Of course, the NAS includes non-airport facilities like Air Route Traffic Control Centers (ARTCC) and Flight Service Stations (FSS) that don't handle take-off and landing, so the low number in the NAS is partly a reflection of the fact that the dataset also contains incidents from such facilities.

The probabilistic causal model shown below in figure-64 identifies three new causal factors that were not part of the Go Around event in the NAS model. The SFO causal model identifies a total of 8 causal factors as significant for Go Around of which only 4 matches with the model for the NAS (the NAS model has only 6 factors). The two new causal factors, “unwritten facility practices” and “poor or outdated design” are specific to the facility and the airspace it serves. Also “event inconsistence with experience” factor could be unique to the facility. A clearance problem involving surface movement which is one of the top issues in the NAS model is not identified as a causal factor for the SFO local model. The interesting result of this model is that unlike the NAS model, there is a significant relationship between the causal factors and the event frequency throughout the two year period (see figure-65).

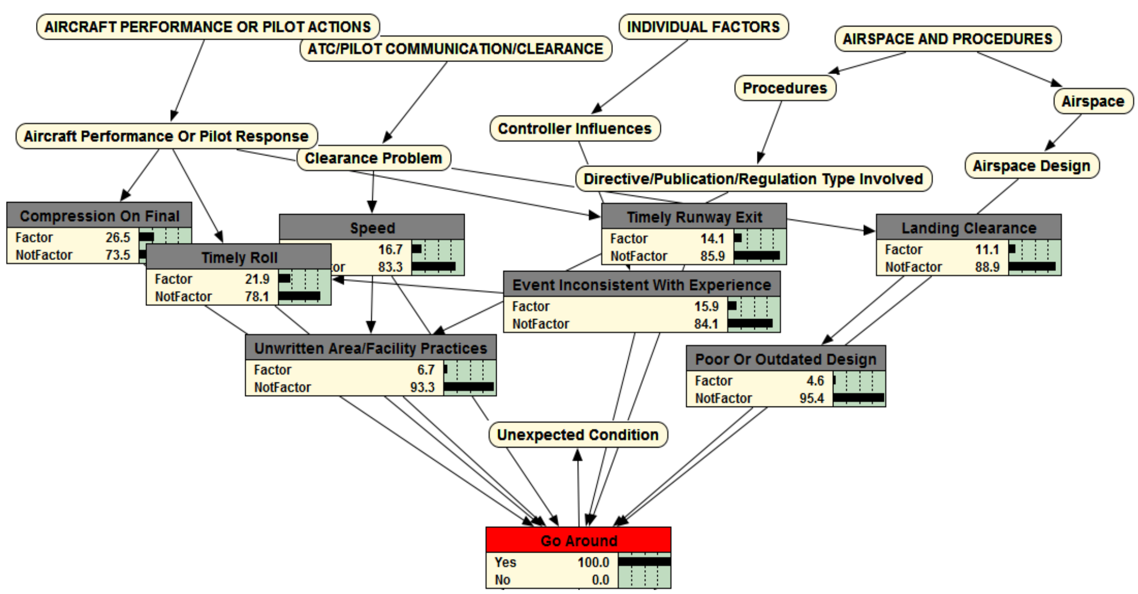


Figure 64: Go Around Probabilistic Network for SFO Facility

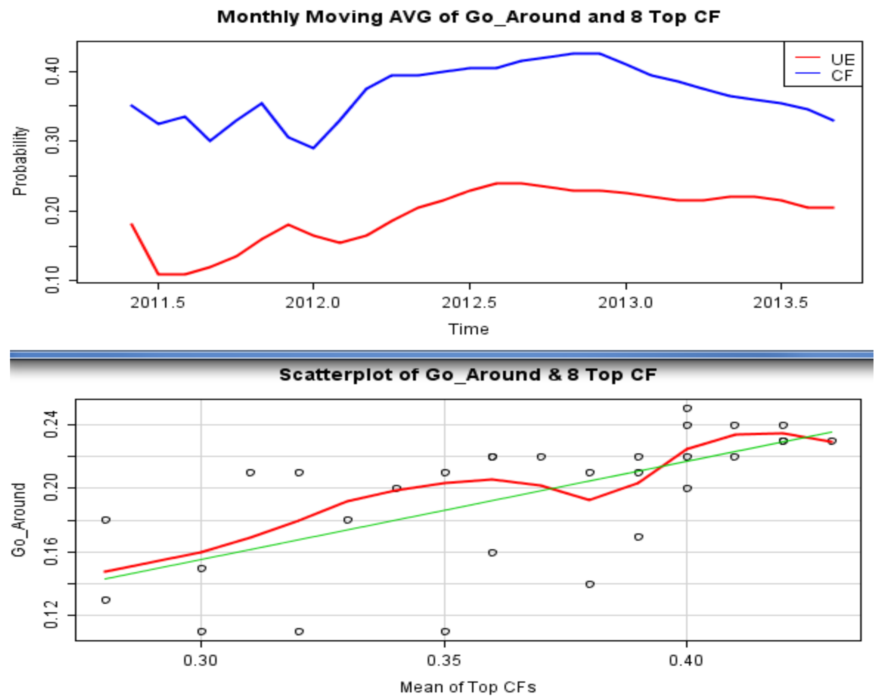


Figure 65: Go Around & Top Causal Factors Correlation for SFO Facility

Therefore, localized models as opposed to general NAS wide analysis maybe more appropriate for some kind of events. However, local models can only be built for facilities with higher volume of data or fragmentation issues reduce the accuracy of the models. Also, locality characteristics may only be better examined after analyzing the NAS wide behaviors of causal factors.

4.4. Common/Generic Factors

As described in the Ranking of common factors section of the methodologies chapter (section 3.5), the listing of the top issues is the result of applying a ranking scheme to all the top causal and/or contributing factors for all ATC-related events modeled in ATSAP dataset. The ranking algorithm is a weight calculation based on the participation of each factor on various events with different severity classification. The algorithm doesn't make any distinction between event types, that is, a runway incursion event is weighted equally with a wake turbulence event as long as the two have the same severity index. It is based on only two parameters, frequency of the participation of the issue in any incident and the severity of the incident. Table-17 shows all the significant factors for the 21 events in ATSAP data according to their rank (weight), but for practical purposes, one may need to pick only the few top items from the list say, top-5, or top-10 to identify the top issues in the NAS. This result is based the lowest level observable variables, but the same approach can identify top issues at higher level abstractions.

Table 18: Top Issues List

Rank	Issue	Catastrophic	Hazardous	Major	Minimal	Minor	None	Weight
1	Controller Actions/Action or Plan Execution	32	52	377	2870	977	41	0.04647
2	Clearance Problem/Altitude	30	50	362	2760	939	39	0.04465
3	Controller Actions/Auditory or Visual Information Misinterpretation	27	44	316	2404	818	34	0.03896
4	Controller Actions/Inadequate Plan of Action Developed	23	38	276	2100	715	30	0.03406
5	Outside Influences/Duty Related Distractions	20	32	234	1777	605	25	0.02883
6	Clearance Problem/Heading	14	23	165	1251	426	18	0.02026
7	Aircraft Performance or Pilot Response/Timely Aircraft Descent or Climb	14	22	159	1209	412	17	0.01958
8	Controller Influences/Lack of Planning with Other Controllers	12	19	137	1039	354	15	0.01676
9	Procedures/Deficiency	11	18	128	971	331	14	0.01570

10	Non-Conformance with a Clearance/Altitude	11	17	123	931	317	14	0.01507
11	Aircraft Performance or Pilot Response/Timely Aircraft Turn	11	17	122	923	314	13	0.01490
12	Non-Conformance with a Clearance/Course	10	17	119	905	308	13	0.01460
13	Information Exchange/Flight Level	10	17	119	901	307	13	0.01456
14	Information Exchange/Special Instructions	10	16	113	854	291	13	0.01384
15	Outside Influences/Airspace Complexity	9	14	102	772	263	11	0.01249
16	Clearance Problem/Cleared Routing	9	14	101	765	261	11	0.01237
17	Aircraft Performance or Pilot Response/Compression on Final	9	14	99	747	255	11	0.01211
18	Information Exchange/Approval Request (APREQ)	8	13	92	695	237	10	0.01118
19	Readback Problem/Altitude	8	12	88	668	228	10	0.01080
20	Information Exchange/Route of Flight	7	11	80	607	207	9	0.00975
21	Non-Conformance with a Clearance/Surface Movement	7	10	73	554	189	8	0.00895
22	Supervisory Influences/Unrealistic Expectations	7	10	73	554	189	8	0.00895
23	Clearance Problem/Take-off	6	10	73	551	188	8	0.00886
24	Aircraft Performance or Pilot Response/Timely Speed Adjustment	6	10	73	549	187	8	0.00886
25	Clearance Problem/Approach Clearance	6	10	67	509	174	8	0.00823
26	Organizational Influences/Inadequate or Lack of Safety Culture	6	10	67	509	174	8	0.00823
27	Policy, Procedure Influences/Inadequate Policy or Procedure	6	10	67	510	174	8	0.00823
28	Policy, Procedural Deficiency/Facility Level	6	9	63	475	162	7	0.00768
29	Loss of Communication/Other Communication Issue	5	9	60	450	154	7	0.00726
30	Clearance Problem/Visual	5	8	57	428	146	7	0.00696

	Separation							
31	Facility Influences/Information Flow	5	8	56	424	145	6	0.00688
32	Clearance Problem/Speed	5	8	55	417	142	6	0.00675
33	Aircraft Performance/Military Activity	5	8	55	415	141	6	0.00671
34	Aircraft Acknowledgement Problem/Acknowledgement not Received	5	8	52	395	135	6	0.00642
35	Flight Data Processing/Flight Plan	4	7	47	352	120	5	0.00566
36	Clearance Problem/Untimely Transfer of Communication	4	7	45	341	116	5	0.00549
37	Supervisory Factors/Policy or Procedural	4	6	44	334	114	5	0.00532
38	Meteorological Conditions/IMC	4	6	42	314	107	5	0.00506
39	Supervisory Influences/Safety or Risk Assessment	4	6	41	313	107	5	0.00502
40	Controller Influences/Over Relying on Automation	4	6	40	298	102	5	0.00481
41	Airspace/Adjacent Airspace, International Providers	4	6	39	297	101	5	0.00481
42	Type of Aircraft/Heavy Jet	4	6	39	291	99	5	0.00468
43	Loss of Communication/Aircraft on Incorrect Frequency	4	6	39	290	99	5	0.00468
44	Airspace Design/Poor or Outdated Design	3	5	31	236	81	4	0.00380
45	Clearance Problem/Landing Clearance	3	5	32	239	82	4	0.00380
46	Aircraft Performance or Pilot Response/Timely Roll	3	5	30	227	78	4	0.00363
47	Equipment Automation/ERAM	3	4	29	215	74	4	0.00342
48	Outside Influences/Airport Surface Conditions	3	4	28	208	71	3	0.00338
49	Aircraft Performance or Pilot Action/Timely Runway Exit	3	4	26	193	66	3	0.00312
50	Special Use Airspace/MOA	3	4	26	192	66	3	0.00312
51	Aircraft Acknowledgement/Wrong Aircraft Acknowledged	3	4	25	185	63	3	0.00300
52	Non-Conformance with a Clearance/Altitude Crossing	2	4	24	180	62	3	0.00291
53	Coordination Ground &	2	4	23	175	60	3	0.00279

	Local/Crossing Active Runway							
54	Runway or Taxiway Condition/Occupied	2	4	23	172	59	3	0.00274
55	Emergency Situation/Pilot Declared	2	3	23	168	58	3	0.00266
56	Aircraft Performance/Small Aircraft	2	3	22	163	56	3	0.00257
57	Equipment/Radar or Surveillance Equipment/Coverage	2	3	20	152	52	3	0.00241
58	Information Exchange/Speeds	2	3	20	148	51	3	0.00236
59	Clearance Problem/Hold Short	2	3	20	146	50	3	0.00232
60	Organizational Influences/Organizational Structure or Chain of Command	2	3	19	141	48	2	0.00224
61	Work Area Influences/Software Design Issue	2	3	18	131	45	2	0.00211
62	Equipment/Malfunction	2	3	17	125	43	2	0.00198
63	Loss of Communication/Poor Coverage or Interference	2	3	16	122	42	2	0.00194
64	Work Area Influences/Equipment Design Issue	2	3	15	113	39	2	0.00181
65	Aircraft Observation Problem	2	2	15	110	38	2	0.00177
66	Emergency Situation/Expedited Handling	2	2	15	111	38	2	0.00177
67	Special Use Airspace/Warning	2	2	14	104	36	2	0.00169
68	Equipment/Radar or Surveillance Equipment Outage	2	2	14	101	35	2	0.00165
69	Equipment/Radar or Surveillance Equipment Malfunction	2	2	13	100	34	2	0.00160
70	Non-Conformance with a Clearance/Speed	2	2	14	100	34	2	0.00160
71	Emergency Situation/Emergency Landing	2	2	13	98	34	2	0.00156
72	Military Activity/Formation Flight	2	2	13	96	33	2	0.00156
73	Special Event/Open Skies/Photo Missions	1	2	12	85	29	2	0.00135
74	Special Use Airspace/ATCAA	1	2	11	80	27	2	0.00127
75	Safety Alert Malfunction/False Alert	1	2	10	74	26	2	0.00118
76	Coordination Ground & Local/Vehicle or Personnel On	1	2	9	63	22	1	0.00101

	Active Runway							
77	Special Event/Skydiving, Ballon, Glider Activity	1	2	8	60	21	1	0.00097
78	Emergency Situation/Controller Declared	1	1	7	52	18	1	0.00080
79	Special Use Airspace/TFR	1	1	7	52	18	1	0.00080
80	Special Event/VIP Movement	1	1	7	51	18	1	0.00076
81	Safety Alert Equipment/LA (MSAW)	1	1	6	41	14	1	0.00063

4.5. Causal-to-Causal Associations

Occasionally, the causal factor identified for a particular event may be non-actionable item. For instance, factors such as duty related distractions are abstract in nature and one can do very little to directly affect them, reduce their frequency or impact. The causal to causal relationship models are mechanisms to treat such causal factors as separate target variables and train probabilistic networks on them to identify other strongly correlated and potentially actionable factors. Hence, although direct intervention may not be possible on a target factor, by indirectly affecting the associated factors the underlying events can be acted up on. One of the downside of identifying causal factors through a manual process, like the Top-5 program, is that it is very difficult to isolate sub-factors for non-actionable items, and hence it usually ignores non-actionable factors. The following outputs list 5 strongly associated causal factors and the corresponding probabilistic networks for three non-actionable factors—duty related distraction, action or plan execution, and information flow.

Table 19: 5 Correlated Factors to Duty Related Distractions

Causal Factor	Description	Prior	Posterior
Outside Influences/Airspace Complexity	Airspace configuration (changing/abnormal) creates undue stress to an individual	0.157	0.447
Supervisory Influences/Unrealistic Expectations	Leadership fails to accurately assess an individual or teams capabilities to accomplish a task	0.034	0.049
Supervisory Factors/Task or Assignment	Inappropriate authorization of an individual to perform a task that is unsafe or beyond the qualifications of the individual	0.023	0.039
Controller Actions/Auditory or Visual Information Misinterpretation	Action towards a particular situation is the result of misinterpreting an auditory cue	0.153	0.17
Work Area Influences/Ambient Noise/Sidebar Conversation	Sound interference with the individual's ability to perform a task	0.02	0.029

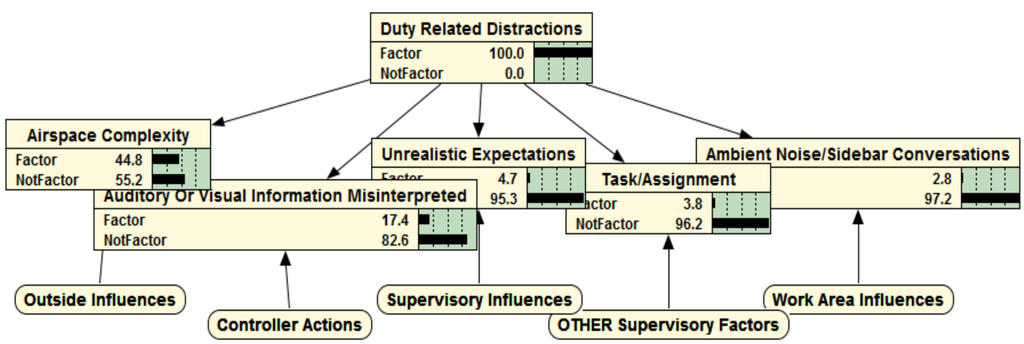


Figure 66: Duty Related Distractions Probabilistic Network

Table 20: 5 Correlated Factors to Action or Plan Execution

Causal Factor	Description	Prior	Posterior
Controller Actions/Inadequate Plan of Action Developed	Risk was not recognized or misjudged and the devised action or plan by the individual is inadequate for the situation	0.209	0.415
Controller Actions/Auditory or	Action towards a particular	0.257	0.385

Visual Information Misinterpretation	situation is the result of misinterpreting an auditory cue		
Clearance Problem/Altitude	Issuing instruction other than what was authorized or intended	0.174	0.202
Clearance Problem/Heading	Issuing a heading instruction other than what was authorized or intended	0.078	0.102
Controller Influences/Lack of Planning with Other Controllers	A lack of planning and coordination with others	0.066	0.067

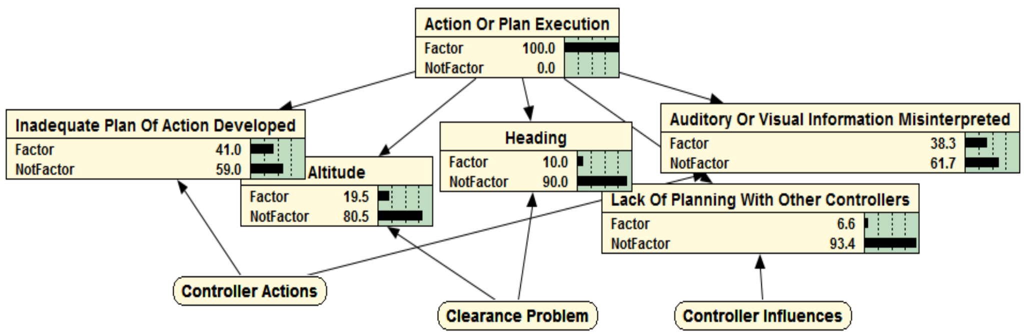


Figure 67: Action or Plan Execution Probabilistic Network

Table 21: 5 Correlated Factors to Information Flow

Causal Factor	Description	Prior	Posterior
Policy, Procedural Deficiency/Facility Level	Lack of, inadequate or out of date presentation of facility operational information to personnel by group leadership	0.03	0.033
Policy, Procedure Influences/Inadequate Policy or Procedure	Group leadership provides inadequate expectations for policy or practice	0.074	0.084
Supervisory Factors/Policy or Procedural	Leadership’s effect on the individual or operation	0.019	0.04
Organizational Influences/Inadequate or Lack of Safety Culture	The unofficial or unspoken rules, values, attitudes, beliefs, or customs of an organization undermine safety performance	0.0311	0.0321
Procedures/Deficiency	A deficient procedure	0.061	0.098

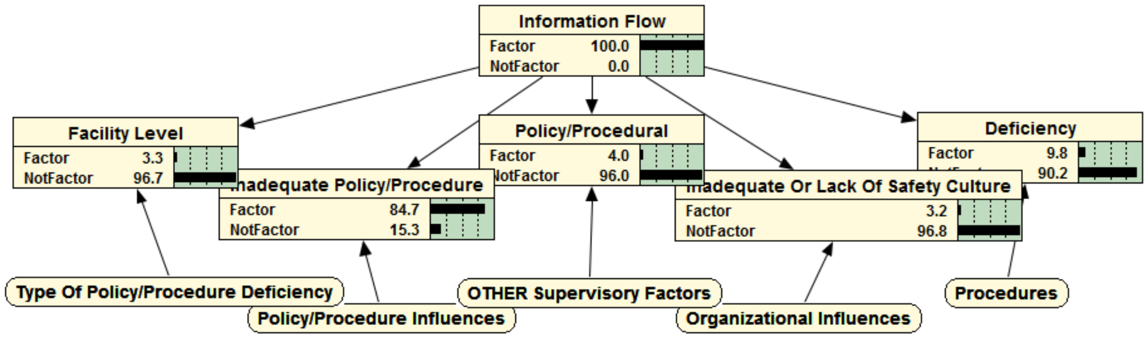


Figure 68: Information Flow Probabilistic Network

5. CONCLUSIONS

This chapter summarizes the background of the problem, the approaches used to deal with the problem, and the research result. The research is primarily focused on the study of ATC-related aviation events and their causal factors based on data from FAA's Air Traffic Safety Action Program (ATSAP). The core of the research is identifying significant causal factors for each event type from a large number of factors using a combination of exiting methodologies and others introduced in this dissertation.

5.1. Two-Phased Factor Selection

The algorithm used to identify the causal factors is a generic method that can be applied in any problem domain with the need to select small number of relevant variables. The purpose of the selection of fewer variables may be for increasing the performance of the target prediction or simplifying the problem by reducing the dimension. One example of such problems is the identification of most relevant factors to diagnose a disease. Unlike analyses that are based on simple frequency counts, this research applies the difference of prior and posterior probabilities to measure the impact of causal factors on individual events. The causal factor identification process follows a two-phased approach. In the first phase, sensitivity analysis is conducted using the difference of prior and posterior probabilities of each causal factor given the particular event being studied. The causal factors are ranked based on such difference, the higher the difference the higher the ranking. In the second phase, naïve Bayes structures are learned incrementally and their prediction performance measured using the reduction of the gain of a Brier score (BS), a probabilistic accuracy metric. When no performance gain is achieved by adding more causal factors to the network, the model learning iteration is stopped and the causal factors that become part of the network nodes constitute the top causal factors.

5.2. Significant Causal Factors

After identifying the significant causal factors, a number of Bayesian networks are created for each event to identify the correlations between the causal factors and the target event. The probabilistic causal models are used to do inference analysis using the knowledge base gained in the trained models. Tree Augmented Naïve (TAN) partial structure learning is used to discover the correlation among the top causal factors. Identifying the correlations in the network is very important in order to use the learned networks for inference analysis. The final Bayesian networks contain not only the top causal factors but also the higher level categories to apply a similar abstraction in the model as used in the real world. The quantification of categories is done using the relative frequency count of each of their low level variables. Incorporating the hierarchical structure is important because in addition to simplifying the overall structure of the models, it adds granularity and facilitates the analysis of the contribution of causal factors at higher levels.

5.3. The Effect of System Changes on Causal Factors

As a dynamic system, the NAS changes, and as a result, the interactions between causal factors and their contributions in causing events change as well. One common approach people use in various domains to reflect the change in a system is to slowly forget the past and make the model mirror the current state of the system. However, analyzing the past in order to understand the nature of the changes of the causal factors and the underlying events in relation to the dynamics in the NAS is important. The approach used in this research is that the aggregate of the causal factors, i.e. the weighted average of the top causal factors are compared against the relative frequency of the respective event. Time series and scatterplots are used to visualize the relationships between the two parameters. When the plots show consistent correlations, it tells us that the changes in NAS have little effect on the causal-effect relationships of the factors and events. However, when there are significant variation between the aggregate top causal factors and the corresponding event, the diversion can be explained by the participation of other factors for the period of time the variation occurs. By studying such changes between factors and events, we can learn more about what set of circumstances lead to the increase or decrease of the rate of event occurrences without the participation of the usual causal factors.

The time series plots of few of the causal models such as IFR to IFR, Unsafe Situation, Go Around, and Terrain show a varying relationship resulting in weaker correlations between aggregate causal factors and the event frequencies. This is a result of changes in the NAS which is partially explained in the result section by creating models for the time interval where the significant variation is observed. That is, by identifying the significant causal factors for the given event only for the time interval with significant variation, further analysis can be done as to why such variations occur. It is beyond the scope of this research to answer questions such as why the frequencies of some events spike or drop without the corresponding change in their top causal factors. However, models for the data points only in that region clearly show the fact that the sudden variations between event frequency and the top causal factors are due to other set of causal factors contributing to that event.

5.4. Common/Generic Factors in the NAS

As the end goal of studying aviation incidents is to improve the overall safety of the NAS irrespective of the type of events involved, this research also introduced an approach that uses the causal factors identified for each event to measure their overall contributions in regard to generic safety issues in the NAS. The relative frequency of each significant casual factor in all event types is combined with the severity index of each event to measure the overall weight of the factors. In aviation risk management, the severity index measures the effect of a particular hazard or incident on the safety of operation. The five standard severity indices are 1 (Catastrophic), 2 (Hazardous), 3 (Major), 4 (Minor), and 5 (Minimal). In addition, the ATSAP program uses additional severity index, 6 (None), to signify effectively no compromise of safety risk. The computed weights which combine the frequency and severity parameters are used to measure the ranking of each issue, and the top issues are determined based on such ranking.

5.5. Non-Actionable Factors

When we identify factors that are significant but no direct viable actions are available to resolve or affect them, we need to resort to indirect methods. One of the challenges in existing approaches followed by hazard identification programs such as the FAA's Top-5 Safety Hazard reporting system is that they completely ignore issues that are non-actionable. The analysis in this research approaches such problems by treating non-actionable factors as target variables and identifying other strongly correlated causal factors. Although such analysis doesn't tell us about the causal-effect correlation, i.e. it doesn't specify which set of factors lead to other set of factors, it enables us discover the existence of the association. As a result, the likelihood of affecting the occurrence of the target causal factors decreases with the increase of our actions on the associated causal factors.

5.6. Intervening in the System

We identify safety issues to act on them. However, the identification usually doesn't specify the optimum set of actions. To identify and take the "best" actions with the available resources at hand, we need decision analysis. In probabilistic models, decision networks are used to identify and quantify the actions by measuring the possible outcomes as a result of our actions. By measuring the various possible outcomes in relations to other constraints, we are able to make optimum decisions. This research demonstrates a decision network on a runway incursion model along with its three top causal factors. It shows the interaction of a combination of generic control and mitigation variables with their numerical utilities in relation to the probability values of the causal factors. The choice of parameters for the utility functions for each action is arbitrary as various assumptions are made. However, with the availability of additional supporting facts in actual decision making settings, the values of those parameters become readily available.

5.7. Summary of Result

The research analysis chapter provides the details of the outputs of the various components in this research. The result includes the top causal factors of 15 events along with their probabilistic models, set of time-based relationships, the ranking of the top issues in the NAS, and the causal-to-causal factors correlations. Events whose relative frequency is below 1% are excluded from the result since there are insufficient data points to make significant observation, such events are rare occurrences. The actual contributions, i.e. probabilistic values, of each top causal factor are displayed in the causal graphical models as well the accompanying tables. The result of each event model is displayed according to the relative frequency of the event occurrences, i.e. events with higher frequencies are listed first in the output. For the first five high frequency events, causal factors involving communication issues, individual factors, aircraft performance or pilot response, and organizational influences play a significant role, hence they constitute the top causal factors. One is referred to the output of each model to understand the correlation and strength of the top causal factors for each event type.

For generic issues in the NAS, the top-5 ATC-related factors, according to the result of this research based on the dataset for the past two years, are primarily factors involving communication issues and individual factors. This result is not particularly surprising given the fact that clearance problems and human factors have been known to cause many ATC issues in the NAS. However, the output in this research provides the quantified probabilistic values to measure the strength of their impact. The top issues are selected from the list of top causal factors in all event types based on frequency and severity index. The following are the top-5 ATC-related issues, from the 3^{rd} level in the causal factor hierarchy, in the NAS based on the data of the ATSAP program in the past two years.

1. Controller Actions/Action or Plan Execution
2. Clearance Problem/Altitude
3. Controller Actions/Auditory or Visual Information Misinterpretation
4. Controller Actions/Inadequate Plan of Action Developed
5. Outside Influences/Duty Related Distractions

As shown here, the top issues contain factors that are non-actionable (e.g. Duty Related Distractions). To take corrective actions directly on such factors would be very difficult. However, based on other strongly correlated factors, it may be possible to resolve or affect the issue indirectly. The following list shows five other strongly associated factors to Duty Related Distractions.

- Outside Influences/Airspace Complexity
- Controller Actions/Auditory or Visual Information Misinterpretation
- Supervisory Influences/Unrealistic Expectations
- Supervisory Factors/Task Assignment
- Work Area Influences/Ambient Noise or Sidebar Conversations

Therefore, instead of ignoring factors that are non-actionable, we can take indirect actions on those factors that have strong association with the top non-actionable factor. Note that the identification of such correlations doesn't not suggest anything about the causal-effect relationship, it only identifies the existence of the correlation.

5.8. Future work

One area for future research on this subject is to device a method to identify the root causes of significant variations in some time intervals of few of the event models between the aggregate causal factors and the event frequencies resulting in weaker relationships. This research answers the question partially by identifying the other set of causal factors contributing to the event in that region, but it doesn't answer why such variations happen. A starting point for such analysis would be to study the effect of seasonality and introduction of new policies, procedures or directives on the interaction between the causal factors and those events that show sudden variations.

Another area for future research is in extending the causal models to decision networks. As this research covers various aspects of aviation safety, identifying top causal factors, gauging the nature of their changes overtime, top issues in the NAS, and decision analysis to make better decisions, it was difficult to provide detailed analysis on some of the components like the decision networks. The decision analysis done in this research is only for demonstration purpose due to scope. A full-fledged decision analysis covering each event model and their factors require a level of effort that can only be achieved through a collaboration work. It requires identifying the control variables for the more than 80 top causal factors in all event types, the mitigation variables of each event, and their quantification, which can be gathered from data and consulting with domain experts. Although it requires a high level effort, the decision analysis component in the analysis of aviation safety is a critical one. The industry and the flying public are directly affected by the day-to-day decisions made in the system so as to make it safer. A data-driven decision making process only enhances that effort.

Another area for future work is to follow a similar approach in analyzing the overall safety of the NAS by merging and mapping the various data sources available in aviation. There is an ongoing effort to have industry-wide common taxonomy across domains. The project includes participating members from regulators, operators, and manufacturers across the world to establish a baseline of hierarchical aviation taxonomy to efficiently analyze the safety of aviation. There is high hope that the effort will succeed, and if that become a reality, it will tremendously improve the efficiency of the analysis of the safety of the NAS using the rich data sources that are available but very difficult to use together currently.

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BIOGRAPHY

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