Modelling the Causation of Accidents: Human Performance Separated System and Human Performance Included System

Von der Fakultät für Bauingenieurwesen und Geodäsie

der Gottfried Wilhelm Leibniz Universität Hannover

zur Erlangung des Grades

Doktor der Ingenieurwissenschaften

Dr.-Ing.

genehmigte Dissertation von

Dipl.-Ing. Yang WANG

2023

Referentin/Referent: Prof. Dr.-Ing. Michael Beer

Korreferentin/Korreferent: Prof. Dr.-Ing. Katharina Klemt-Albert

Tag der Promotion:

26.05.2023

Kurzfassung

Jedes Jahr ereignen sich weltweit Millionen von Arbeitsunfällen, die zahlreiche Opfer fordern und enorme wirtschaftliche Verluste zur Folge haben. Vorangegangene Studien aus dem Feld der Risikoeinschätzung zeigten, dass es wichtig ist die Wahrscheinlichkeit von Faktoren, welche zum Auftreten von Unfällen beitragen, zu quantifizieren. Mehrere Methoden, wie z. B. die Technik zur Vorhersage der menschlichen Fehlerrate (*Technique for Human Error Rate Prediction*, THERP), wurden dafür vorgeschlagen, potenzielle Risikofaktoren zu bewerten und die Systemsicherheit zu verbessern. Diese Methoden haben jedoch einige Einschränkungen, wie z.B. ihre geringe Generalisierbarkeit, die Behandlung von Unfallursachen und menschlichem Einfluss als zwei voneinander getrennte Forschungsthemen, die Notwendigkeit ausgiebiger Datensätze, oder die ausschließliche Abhängigkeit von Expertenwissen.

Um diese Einschränkungen zu überwinden, 1) klassifiziert diese Dissertation die Systeme in zwei Kategorien. Zum einen in von menschlichem Einfluss separierte Systeme (*Human Performance Separated System*, HPSS) und zum anderen in Systeme mit menschlichem Einfluss (*Human Performance Included System*, HPIS); 2) entwickelt ein auf Bayes'schen Netzwerken (BN) basierendes Unfallkausalitätsmodell, das auf beide Arten von Systemen angewendet werden kann, um den Einfluss menschlicher Wahrnehmung in HPSS und den Einfluss menschlichen Versagens in HPIS zu untersuchen; 3) untersucht zwei Methoden zur Analyse menschlichen Versagens. Die erste Methode geht von einer kognitiven Wahrnehmung aus und die zweite behandelt das menschliche Versagen als essenziellen Teil des Systems. 4) schlägt eine innovative Taxonomie namens *Contributors Taxonomy for construction Occupational Accidents* (CTCOA) für HPIS vor, die nicht nur auf die Unfallkausalität abzielt, sondern auch zur Rückverfolgung menschlichen Versagens im Bauwesen verwendet werden kann. 5) erstellt BN-

Beispielmodelle aus unterschiedlichen Industriesektoren. Dazu zählen Gasturbinenausfälle als typisches Beispiel für HPSS-Maschinenversagen, das *Multi-Attribute Technological Accidents Dataset* (MATA-D) für einfaches HPIS-Systemversagen und das *Contributors to Construction Occupational Accidents Dataset* (CCOAD) für komplexes HPIS-Systemversagen. Diese drei BN-Modelle zeigen, wie die von uns vorgeschlagene Methode in Bezug auf spezifische Probleme aus verschiedenen Industriesektoren angepasst und angewendet werden kann.

Unsere Analyse zeigt die Effizienz der Kombination von Expertenwissen und mathematischer Unabhängigkeitsanalyse bei der Identifizierung der wichtigsten Abhängigkeitsbeziehungen innerhalb der BN-Struktur. Vor der Parameteridentifizierung auf Basis von Expertenwissen sollten die Auswirkungen der menschlichen Wahrnehmung auf die Modellparameter gemessen werden. Die vorgeschlagene Methodik basierend auf der Kombination der menschlichen Zuverlässigkeitsanalyse mit statistischen Analysen kann zur Untersuchung menschlichen Versagens eingesetzt werden.

Schlüsselwörter: Unfallkausalitätsmodell, Menschlichem Einfluss, Bayes‘schen Netzwerken, menschlichem Einfluss separierte Systeme, Systeme mit menschlichem Einfluss

ABSTRACT

Millions of work-related accidents occur each year around the world, leading to a large number of deaths, injuries, and a huge economic cost. Previous studies on risk assessment have revealed that it is important to calculate the probabilities of factors that can contribute to the occurrence of accidents. Several methods, such as the Technique for Human Error Rate Prediction (THERP), have been proposed to evaluate potential risk factors and to improve system safety. However, these methods have some limitations, such as their low generalizability, treating accident causation and human factor as two separate research topics, requiring intensive data, or relying solely on expert judgement.

To address these limitations, this dissertation 1) classifies systems into two types, Human Performance Separated System (HPSS) and Human Performance Included System (HPIS), depending on whether the system involves human performance; 2) develops accident causal models based on Bayesian Network (BN) that can be applied to both types of systems while examining the influence of human perception in HPSS and human errors in HPIS; 3) examines two methods for the analysis of human errors with the first method based on the cognitive view and the other method treating human errors as an essential part of the system; 4) proposes an innovative taxonomy as an example for HPIS, known as the Contributors Taxonomy for Construction Occupational Accidents (CTCOA), which not only targeting accident causation, but can also be used for tracking human error in construction; 5) builds example BN models in the different industrial sectors, including gas turbine failures as a typical example of HPSS machine failures, Multi-Attribute Technological Accidents Dataset (MATA-D) as simple HPIS failures, and Contributors to Construction Occupational Accidents Dataset (CCOAD) as complex HPIS failures. These three types of BN models demonstrate how our proposed methodology can be adapted to specific questions and how it can be applied in various industrial sectors.

Our analysis demonstrates that it is efficient to combine expert judgement with mathematical independence analysis to identify the main dependency links for the BN structure in all models. The influence of human perception on model parameters should be measured before these parameters being identified based on expert judgement. Our proposed methodology can be used to study human errors by combining traditional human reliability analysis with statistical analysis.

Keywords: Accident causation model, Human error, Bayesian network, Human performance separated system, Human performance included system

Table of Contents

List of Abbreviations

- BN - Bayesian Network
- CCOAD - Contributors to Construction Occupational Accidents Dataset
- CPD - Conditional Probability Distribution
- CPT - Conditional Probability Tables
- CREAM - Cognitive Reliability and Error Analysis Method
- DAG -Directed Acyclic Graph
- DCS -Digital Control System
- HEP - Human Error Probabilities
- HFE - Human Failure Event
- HPSS - Human Performance Separated System
- HPIS - Human Performance Included System
- HRA - Human Reliability Analysis
- MATA-D - Multi-Attribute Technological Accidents Dataset
- MAUD - Multi-Attribute Utility Decomposition
- MOF - Management and Organizational Factors
- MPT - Marginal Probability Table
- PPE - Personal Protective Equipment
- PRA - Probabilistic Risk Assessment
- PSA - Probabilistic Safety Assessment
- SLI - Success Likelihood Index
- SLIM - Success Likelihood Index Method
- SPAR-H - Standardised Plant Analysis Risk-Human reliability analysis
- THERP - Technique for Human Error Rate Prediction
- TRC - Time Reliability Correlation
- UPS - Uninterruptible Power Supply

This page intentionally left blank.

Chapter 1. Introduction

1.1 Background

The International Labour Organisation (ILO) estimates that there are approximately 340 million work-related accidents and 160 million fatalities of work-related illnesses every year. Among them, there are about 2.3 million humans around the world who succumb to work-related accidents or diseases every year (ILO, 2022). In developed countries, such as the United States of America (USA), 1,133 reported work-related fatalities in 2020 among cases inspected by the Federal or State Occupational Safety and Health Administration (Department of Labour of USA, 2021). In the United Kingdom (UK), the manufacturing industry caused 27 deaths of workers between 2019 and 2020 (Health & Safety Executive, 2021). In 2020, more than 44,000 cases involved machine failures in the UK, including 2% to 6% of which reported nonfatal and fatal injuries (Nicola Laver LLB, 2020). In Germany, 2,187 fatal accidents at work in the commercial sector (excluding mining and public roads) were reported to the Federal Institute for Occupational Safety and Health (BauA) during 2009 to 2021, of which 40% occur at construction sites (Federal Institute for Occupational Safety and Health (BauA), 2022). In developing countries, such as China, about 34,600 occupational accidents occurred in 2021, causing 26,307 deaths in the industry (National Bureau of Statistics of China, 2022), including 356 accidents and 503 fatal injuries in the mining industry (National Mine Safety Administration of China, 2022). In the first half-year of 2018, 1,732 accidents and 1,752 deaths were reported in the construction industry of China (Work Safety Commission of the State Council, 2018).

Previous studies revealed that some of these accidents were simply caused by machine failure, while the others were complex with multi-attributes, arising from the interaction between workers and equipment, tools, techniques, and technologies. For example, McCafferty (1995) revealed that 80% of the accidents in the US's offshore gas and oil facilities were human-induced and occur in the operations departments. Harati-Mokhtari (2007) had shown that 80 to 85% of all recorded maritime accidents between 1991 and 2001 are directly due to or associated with human errors. Wang (2015) pointed out that human errors play a major role in rail crack incidents. Therefore, it is important to understand the influence of human factors to ensure safe operations of engineering systems and minimise the chance of catastrophic consequences.

The term 'human factor' is typically used to refer to complex relationships and interactions between humans and the surrounding environment, organizations, tasks, and technologies (Dhillon, 1986; Hollnagel, 1998; Swain & Guttman, 1983). Previous studies have suggested that Human Reliability Analysis (HRA) should be conducted to assess the probability of human failure events (HFEs) and to estimate the probability of human errors (Aguilar & West, 2000; K.M. Groth & A. Mosleh, 2009).

However, despite the variety of HRA methods available to estimate the probability associated with human factors, these methods treat accidents as direct consequences of human errors while ignoring the influence of other factors on accidents. Furthermore, due to the lack of data, these methods require data obtained from expert judgement with relevant experiences and knowledge, which may be confounded by expert bias. Thus, probabilities tools, in particular the Bayesian Network (BN), are receiving increasing attention in the field. However, the evaluation of conditional probability tables (CPTs) of BN requires more data to capture all possible conditions specified in the model. In these cases, this research has focused on developing a BN-based methodology to enable combining expert judgement with empirical data-driven analysis. This dissertation examines whether the proposed methodology could identify risk factors using previously collected datasets and a new dataset of construction accidents.

This dissertation is organised as follows: Chapter 1 reviewed the theoretical background and research gaps in accident causation modelling and specified the objectives of this dissertation. Chapter 2 introduced the Bayesian Network, including its mathematical foundation, modelling process, and inference procedure. Chapter 3 reported the failure assessment modelling procedure for the Human Performance Separated System (HPSS) and an idea to explore the influence of human perception in this model. Chapter 4 built an example BN model for gas turbine failure by following Chapter 3. Chapter 5 reported the idea of a failure assessment model for the Human Performance Included System (HPIS) and explored the influence of human errors in two methods. Chapter 6 built an example BN model of human errors by following Chapter 5 and revealed weights of the major contributors to human errors from a cognitive point of view. Chapter 7 presented an example BN model of HPIS by using data that were built from occupational accidents in the construction industry in China. It also reported on analysis of human errors by following Chapter 5. Chapter 8 summarized the findings, contributions, and limitations of this dissertation, and directions for future studies.

1.2 Accident Causation Model and Human Reliability Analysis

1.2.1 Accident Causation Models

1.2.1.1 Definition

Accidents are unintended and unwanted events with catastrophic consequences that are related to mechanical failures or human errors (Moura et al., 2017). Accident causation models are used to identify hazards, implement post-accident accountability, prevent imminent accidents, and improve safety awareness of the public and workers (Dhalmahapatra, Das, & Maiti, 2022). Most accident causation models aim to address two key questions: a) what are the causes of the accident? B) how does the accident happen? These models aim to not only form the theoretical foundation for the growing safety science and but also provide essential methods for accident prevention and analysis (Fu et al., 2020).

1.2.1.2 Types of Accident Causation Models

Accident causal models can be classified into nonlinear and linear models (Fu et al., 2020; Yan, Chi, & Lai, 2020). Linear accident causation models study the causes of accidents at different stages to form a chain using logical sequences. On the contrary, nonlinear accident causation models do not distinguish causes of accidents at different stages, but focus on different aspects of accidents, such as statistics, energy, system, and human (Fu et al., 2020). For example, statistics-based accident models employ accident statistics to examine the connection between the severity and the number of accidents. Energy-based accident models consider energy transfer and release as study objects to suggest associated measures. System-based accident models are recent models that include all factors related to the accident in the analysis. Human-based accident models focus on human factors (Yan, Chi, & Lai, 2020). Woolley, Goode, Read, and Salmon (2019) argued that accident causation models can also be classified into simple linear models, complex linear models, and complex nonlinear models.

Simple linear models, such as Heinrich's Domino Theory (Heinrich & Herbert William, 1931), assume that an accident is the outcome of several sequential causes, including social, environmental, and individual factors (Wang & Yan, 2019)**.** Social ancestry or environment, personal fault, unsafe actions, physical and mechanical hazards, accident, and injury are five critical factors that result in an eventual accident (Dwi Wicaksono et al., 2022). Accidents are usually caused by one of the factors falling with a continuing impact of the explosion, which ultimately results in the accident. Any eliminations of dominos (interruption of the knockdown impact) can avoid or stop the accident. Li, Zhang, and Peng (2021) states that mechanical vulnerabilities and unsafe actions are central factors in the sequence of an accident. Fault Tree Analysis (FTA) is the logic based on the multicausality principle that uses symbols, identifiers, and labels to trace event branches with the capacity to contribute to the accident. Budiyanto and Fernanda (2020) argued that the root causes of each risk category should be determined through a top-down approach. The top event (undesired events of interest) is identified before the conditions of direct causal fault leading to such an event are revealed. When the order of fault dependencies or primary failures are identified, the accident may be stopped (Ahn et al., 2021). Therefore, removing human errors as the cause of several accidents makes any previous factors ineffective (Dunlap, Basford & Smith, 2019).

Complex linear models presume that accidents blend several unsafe factors and conditions in which the individual interacts closely with the at-risk system. Methods of accident avoidance developed from the initial sequential focus to finding original causes of accidents, elimination, and establishment of barriers to encapsulating such causes. The accident is preventable by forming the correct controls (Hasan, Chatwin, & Sayed, 2019).

The most prominent complex linear models are the generic epidemiological, time sequence, systemic, systems safety, and Reason's "Swiss Cheese" model (Stretton, 2020). For instance, the Swiss-Cheese model conceptualises the system with imperfect defence layers to detect and prevent errors. The layers are characterised by latent and active failures (holes) or rare conjunctions in successive defences that permit hazards that damage contact with assets and people (Joe-Asare, Amegbey, & Stemn 2020). The model identifies the probabilities of organisational factors that cause accidents. However, complex linear models do not offer clear explanations for the occurrence of causal factors of accidents (Bode & Vraga, 2021). Instead, accidents arise from interrelating variables in actual environments (Eric Hollnagel, 1998). Understanding the interacting variables helps prevent accidents (Alders, Rafferty, & Anderson, 2022).

Complex nonlinear models include the Functional Resonance Accident Model (FRAM) (Erik Hollnagel, 2012b) and Systems-Theoretic Accident Model and Processes (STAMP) (Diop, Abdul-Nour, & Komljenovic, 2022). The FRAM offers approaches to describing outcomes using the resonance idea of the unpredictability of regular performance (Choi & Ham, 2020). It uses four steps of describing functional resonance and variability, and damping unwelcome variability, including a) describing and identifying vital system functions before characterising every function by means of six fundamental aspects (characteristics); b) checking the model consistency or completeness; characterise likely variability of model functions and the possible natural variability of model functions; c) describing functional resonances based on couplings or dependencies amongst functions as well as the capacity of functional variabilities; d) and identifying the manner of monitoring resonance development (dampen the variability for unwanted results or amplify the variability for wanted results) (David, Schraagen, & Endedijk, 2022).

Recently, machine learning has also attracted some attention in building accident models (Kim et al., 2022; Matías et al., 2008; Morais, et al., 2022; Zhu et al., 2021). For example, Kim et al. (2021, 2022) pointed out that the statistical analysis method can hardly reflect the nonlinear characteristics of accidents determined by complex influencing factors, like in the construction industry, and developed machine learning models for construction safety accidents as well as container port accidents, which performs better than a conventional multi-regression model. Infante (2022) compared machine learning models with statistical models on road traffic accident severity classification and found that, with a small sample of imbalanced data, machine learning models generally do not perform better than statistical models; however, they function similarly when the sample is large and has a slight imbalance. Morais et al. (2022) used machine learning algorithms to classify accident reports from different sectors and compared the results with human experts. These studies have revealed that it is feasible to use artificial intelligence to collect data for risk and reliability assessment.

1.2.2 Human Reliability Analysis

Previous studies have revealed that human reliability analysis (HRA) can be used as a structured method to identify human failure events (HFEs) and estimate the probability of those events. The probabilities used to evaluate HFEs are known as Human Error Probabilities or HEPs (Gao, Su, Qian, & Pan, 2022). There are multiple methods used for HRA, including Technique for Human Error Rate Prediction (THERP) (Swain & Guttman, 1983), Time Reliability Correlation (TRC) (Hall, Fragola, & Wreathall, 1982), Cognitive Reliability and Error Analysis Method (CREAM) (Hollnagel, 1998), Standardised Plant Analysis Risk-Human Reliability Analysis (SPAR-H) (Gertman et al., 2004), Success Likelihood Index Method/Multi-Attribute Utility Decomposition (SLIM/MAUD) (Rosa, Humphreys, Spettell & Embrey.,1985), and Bayesian Network (Bruce Hallbert, Kolaczkowski, & Lois 2007).

1.2.2.1 Technique for Human Error Rate Prediction (THERP)

Swain and Guttman (1983) proposed the THERP initially for human reliability assessment in the nuclear industry using a fault-tree approach. In recent years, THERP has been expanded to evaluate the probability of human errors occurring throughout the interaction between human and machine systems in other hazardous industries. THERP is used to reduce the likelihood of occurrence of these errors and to improve overall system safety. THERP is the first-generation HRA approach with an event tree modelling base where every limb signifies a blend of people's actions, impact, and outcomes of the actions. Zhang, Zhu, Hou, and Liu (2021) stated that one advantage of the THERP method lies in its ability to assess human error rate for system failures. It is particularly efficient in assessing human reliability for routine tasks (Farcasiu & Constantinescu 2021). However, THERP has some limitations, including being resource intensive, time consuming, limited performance shaping factors (PSF), and reliance on subjective expert judgement to identify causal links (Dsouza & LU, 2016).

1.2.2.2 Time Reliability Correlation (TRC)

According to Hall (1982), the TRC is used to quantify the diagnosis of HFEs based on available time and adjustments of human responses by considering PSFs in a risk analysis. Institutions and researchers use TRC to quantify human failure after an irregular event. Data are derivable either from expert judgement or quantitative analysis.

The simulator information leads to the advancement of TRC systems based on the uncertainty of the model and the positive response time. Variability in workers, job-linked characteristics, and particular events place a vital uncertainty on response prediction (distributed response time) (Bona et al., 2021). There is a need to quantify the response time with the time-dependent distributions after considering the adequate response time in the median response time because it is a vital factor for identifying the leading behaviour connected to human action that underlies the response time. Sufficient response time influences response reliability and post-initiator response (Jung & Park 2020). However, the response time is not available in many accidents reports for the TRC.

1.2.2.3 Standardised Plant Analysis Risk-Human Reliability Analysis (SPAR-H)

According to Gertman et al. (2004), the SPAR-H model merges elements of information processing and stimulus-response approaches because to undertake actions repeatedly identified in procedures fruitfully, HRA analysts must have the capacity to take planning and diagnosis aspects as well as a possibility of operator ability into consideration. Chen, Zhang, Qing, and Liu (2021) argued that the distinction between information processing (diagnosis) and response (action) forms the foundation for distinct action and diagnosis worksheets with distinct calculations of probability.

Furthermore, the SPAR-H acknowledges the role of environmental factors in action and diagnosis. For instance, analysts can note during performance evaluations, but interactions or factors are hard to examine because of the complexity, deceptive indications, time-reliant aspects, and/or impact of faulted or unavailable equipment combinations (Liu et al., 2021). The SPAR-H includes the following steps: a) Step 1 Categorising the HFE as action and/or Diagnosis; b) Step 2 Rating the PSFs (existing time, stressors and stress, complexity, training and experience, procedures, human-machine interface and ergonomics, duty fitness, office processes); c) Step 3 Calculating the PSF-amended HEP; d) Step 4 Calculating Dependence Accountability and e) Step 5 Setting the minimum cut-off value (Murchison & Gilmore, 2018).

The main components in SPAR-H including: a) A flow of information from the environment through diverse sensing modalities (visual, kinaesthetic, and auditory). Environmental aspects filter information; b) Detection (direct and simple perception, recognition, and identification); c) Task demand characteristics that impact an operator's internal resources; d) Situational and environmental factors that contribute to the failure or success of people's performance by considering effects upon processing, response and perception (Krymsky & Akhmedzhanov, 2021).

However, SPAR-H is not ideal for realistic and detailed analysis of empirical data since it contains only eight PSFs, which cannot cover the complexity of many accidents. Although previous research argued that PSFs should be expanded, there is no explicit guidance on how to calculate or estimate the probabilities associated with the events (Julie Bell & Justin Holroyd 2009).

1.2.2.4 Success Likelihood Index Method/Multi-Attribute Utility Decomposition (SLIM/MAUD)

According to Rosa, Humphreys, Spettell & Embrey (1985), SLIM/MAUD uses a MAUD (interactive computer-based) procedure for organising and extracting professional opinions and guessing HEPs. The simple justification underlying SLIM/MAUD is that the combined effect of relatively small PSFs determines the probability of error in particular situations. Silva, Oliveira, and Veronese (da Silva et al., 2021) contend that experts can assess each PSF's relative weight or importance using its impact on task reliability. The main assumption is that experts give numerical ratings indicating excellent or bad PSFs as independent assessment in a task of relative importance. 'Good' refers means the PSFs are enhancing reliability while 'bad' refers to the degrading of reliability (Pan & Wu 2020). Upon attaining the weight and rating's relative importance, SLIM/MAUD multiplies them with every PSF and sums the resulting product to cause Success Likelihood Index (SLI).

SLI is the quantity representing the complete confidence of the judges in negative or positive PSF effects on the probability of the task's success (Norazahar, 2020). The assumption is that in the long run, SLI is connected to the observed likelihood of success in situations of interest (actuarially determined probability) because judges have experience, knowledge, and accurate awareness of the effect of PSF on the possibility of success (Jamshidi, 2020). The evaluation of two available tasks with a known probability of success is to create an observed calibration relation between the log of task-success probability and SLI in the evaluated set (P. Liu & Liu 2020). The recommended logarithmic form relationship is Log p (win) = an (SLI) + b for the transformation of SLIs into the HEPs; wherein b and a are constants that are empirically resultant.

The occurrence of such a condition means that the *b* and constants in the equation above are transformable by the judges into logarithmic probability of task success and SLI values. Then, the log-likelihood of success is easily converted into success probability (Santiasih & Ratriwardhani, 2021). The SLIM procedure comprises an assortment of the professional panel, subset, and situation definition, PSF elicitation, task rating on the PSF scaling, elicitation of ideal-point and calculation scaling, checks on independence, procedures of weighting, SLIs calculation, SLIs conversion into needed probabilities, uncertainty-bound scrutiny, sensitivity study for purposes of error-reduction research and process of documentation (Liu & Liu 2020; Jamshidi & Sadeghi, 2021).

However, SLIM is highly dependent on expert judgement, which requires a panel of experts. When there is a lack of data, it is difficult to calibrate the SLIs (Julie Bell & Justin Holroyd 2009).

1.2.2.5 Cognitive Reliability and Error Analysis Method (CREAM)

In 1998, Erik Hollnagel developed the CREAM to maintain divisions between the logical consequences and causes of human errors (Hollnagel, 1998; Pasquale et al., 2013). The CREAM holds that occurrences of a particular behaviour are the leading causes of people's subsequent responses leading to catastrophic consequences. CREAM allows: a) Identification of tasks, actions, or work in need or dependent on people's cognition and are impacted by cognitive reliability variations; b) Determination of conditions for reducing cognition reliability, and conditions for increased risk for actions; c) Provision of appraisal on system safety or human performance significances employable in Probabilistic Safety Assessment (PSA) or Probabilistic Risk Assessment (PRA); d) Development and specification of modifications which improve conditions, increase cognition reliability, and risk reduction. Sharma and Rai (2021) find that CREAM is a model, method, and classification scheme that can be employed a) predictively for the prediction of likely human errors, and b) retrospectively for error analysis and quantification. Slim and Nadeau contend that CREAM is a timely and valuable HRA to present error taxonomies based on cognitive engineering principles to integrate organizational, individual, and technological features (Slim & Nadeau, 2020).

CREAM is used as the second-generation HRA approach for probabilistic safety assessment (PSA) or stand-alone accident analysis and is part of the larger interactive systems design methodology (Hollnagel, 1998). In addition to offering an essential theoretical base, CREAM provides a graduated explanation of how to employ a context-dependent cognitive model to establish how taxonomy applies to the analysis and the prediction of performance (Abolfazl, Abdolnaser & Iraj, 2020). CREAM enables risk analysts and system designers to a) identify tasks dependent on people's cognitive reliability and in need of people's cognition; b) determine circumstances for risk reduction and cognitive reliability; and c) provide assessments of the human performance consequences on the safety of the system (Vladykina & Thurner, 2019).

However, as Hollnagel (2012) pointed out that CREAM focuses on: a) How actions can fail, rather than on the variability of performance; b) One part or component of the system only, namely the human(s). Thus, data analysed in the CREAM cannot be used to predict accidents.

1.2.2.6 Bayesian Network

Recently, the Bayesian Network (BN) approach to HRA has received increasing attention. BN is a graphical model that represents and quantifies probabilistic relationships among factors in a directed graph. It has been recognised as an appropriate method for uncovering overall causal structure for scarce, multisource data, potentially improving both the estimation of human error probabilities and the underlying assumptions in the quantitative algorithms employed by the different HRA methods (Bruce et al., 2007). Mkrtchyan, Podofillini and Dang (2015) indicated that the BN approach can combine different sources of information, potentially allowing the development of more robust HRA models based on cognitive theory and empirical data. They grouped the BN approach within the HRA domain in two directions: a) several studies use the BN ability to model multilevel influences of Management and Organizational Factors (MOF) on human errors; b) some contributions proposed BN versions of existing HRA models, such as SPAR-H and CREAM (Mkrtchyan, Podofillini, & Dang, 2014).

1.3 Research Gaps

Accidents are rather complex events. The mechanism behind them may differ from that of the industrial sectors. The triggers might be human carelessness, a failure of a component, or a combination of various causes. It is difficult to build a universal model for all kinds of accidents. Finding a universal methodology is important to provide a potential solution for industrial sectors. However, there are some research gaps in this field.

First, there are few studies on the combination of causation modelling and HRA. In the present, accident causation modelling and HRA are studied as two separate research topics. The former focuses on linear or non-linear mechanisms and aims to find the trigger(s). The latter pays more attention to the human condition, including performance variability and cognition, to improve human reliability (Podofillini & Dang, 2017). Since human factors are core components in many systems, but not in all of them, a universal methodology for accident modelling should include HRA. However, they are still separated.

Second, traditional accident models value the importance of logical reasoning, but do not focus on the quantity and quality of data. Logical reasoning does not work well for complex systems. A numerical model is more powerful but requires sufficient data. However, these data are not available in many industrial sectors, especially complex systems such as construction industry.

Third, traditional HRA methods await for improvement in several aspects: 1) Extending method scope, such as including different types of errors and other industrial sectors; 2) Collecting more empirical data that have a stronger basis on cognitive models; 3) Applying to advanced human-machine interfaces; 4) Conducting more structured and detailed qualitative analyses, and 5) Forming more empirically-based representation of the failure influencing factors (Mkrtchyan, Podofillini, & Dang, 2015).

1.4 Scopes and Goals

This dissertation focuses on the quantitative modelling demands of the accident model. It aims to develop a universal methodology and procedure for the industry. Models using this methodology are expected to deal with both simple and complex accidents while accounting for human factors when relevant.

In this dissertation, an accident is treated as a system failure. The proposed methodology will locate which part(s) of the system has a greater chance of being abnormal (or irregular) and which part(s) shows more influence on the whole system than others. One innovation of this methodology is that we classify systems into two types, known as Human Performance Separated System (HPSS) and Human Performance Included System (HPIS). The former is similar to a hardware system which does not involve human organization or human performance. For instance, an engine, a ship, a spaceship, etc. This type of system only requires minimal involvement of human, for example telling it to start working or stop working, but the orders is not a part of the system. In contrast, HPIS, it not only contains the hardware but also some complex factors, such as human performance and human organisation. Although systems differ from sector to sector, our proposed methodology allows us to explore the accident from the same pipeline regardless of the industrial sectors. For example, in the construction industry, HPSS is a product itself, such as a bridge, a tunnel, or a house, which does not concern building and maintaining it while HPIS is the process of building or maintaining the product. To model HPSS, we first dismember it and then observe every component, every part, and every function. To model HPIS, HRA is a core part, and this dissertation focuses on human performance during operation but not during the design of the system. Thus, our methodology can both include or exclude HRA depending on the type of target system.

Importantly, our methodology combines expert knowledge with statistical data analysis. The models using this methodology can exploit the potential use of limit data to overcome the shortage of the traditional model. It can also deal with the lack of data in many industrial sectors with the help of expert knowledge. Our methodology will reveal the most influential contributors to the system and quantify the probabilities of components and system failures. We will test our methodology in case studies, as reported in Chapters 4,6 &7.

Furthermore, our methodology will improve HRA in several ways:

1) It allows us to explore the human factor from different angles by forming different system structures. This dissertation shows two possible angles, explores what is behind

human errors from the cognitive point of view, and examines the role of human errors in HPIS.

2) It provides guidelines for data collection and expansion (see Chapter 6&7).

3) It is a more structured and detailed qualitative analysis. The models based on it have clear graph structures and can quantify the causation. Despite the imprecision of quantification with data access limitation, the models can tell more details.

Chapter 2. Overview of the Bayesian Network

This chapter first introduces the probability theory that forms the mathematical foundation of the Bayesian Network (BN) that is used to model the causation of accidents in this dissertation. Then, it reviews the BN theory and demonstrates the procedure for building a BN model. Finally, it presents two types of inference analysis, including predictive analysis and diagnostic analysis, that are used to identify the most probable consequence or the most important contributors of accidents.

2.1. Probability Theory

This section introduces key concepts and principles of the probability theory that serves as the mathematical framework of the BN.

2.1.1. Total Probability

The law of total probability (Zwillinger, 2019) is a theorem that states if $\{Y: y = 1,2,3, \dots, n\}$ is a finite or countably infinite partition of a sample space (in other words, a set of pairwise disjoint events whose union is the entire sample space), and each event $Y(y)$ is measurable, then for any event Z of the same probability space:

$$P(Z) = \sum_{y=1}^{n} P(Y_y, Z) \qquad \textit{Equation 2-1}$$

In which $P(Y_y, Z)$ is the joint probability that events Y_y and Z occur.

2.1.2. Conditional Probability

Conditional probability is a measure of the probability that an event is occurring – given that another event has happened (by assumption, presumption, assertion, or evidence) happened (Allan Gut, 2013). If the event of interest is X and the event Y is known or assumed to have occurred, 'the conditional probability of X given Y' or 'the probability of X under condition Y' is usually written as $P(X/Y)$ (Probability and Statistics Symbols). The mathematical definition of $P(X/Y)$ is as the following equation (Kolmogorov & Bharucha-Reid, 1956):

$$P(X/Y) = P(X,Y)/P(Y) \quad \textit{Equation 2-2}$$

With a formula translation, this axiom can also be defined as follows:

$$P(X,Y) = P(X/Y)P(Y) \quad \textit{Equation 2-3}$$

For three variables, such as the conditional probability of X given Y and Z, the axiom can be expressed as follows:

$$P(X,Y,Z) = P(X/(Y,Z))P(Y,Z) \quad \textit{Equation 2-4}$$

If event Y and event Z are independent, then the equation is translated to

$$P(X,Y,Z) = P(X/(Y,Z))P(Y)P(Z) \quad \textit{Equation 2-5}$$

2.1.3. Marginal Probability

Contrary to conditional probability, the marginal probability is the probability that a single event will occur, independently of other events. According to the law of total probability (Zwillinger, 2019):

$$P(X) = \sum_{y=1}^{n} P(X,Y_y)/P(Y_y) \quad \textit{Equation 2-6}$$

2.1.4. Bayesian Theorem

The Bayesian theorem is stated mathematically as the following equation (Stuart and Ord, 1994):

$$P(Y/X) = \frac{P(X/Y)P(Y)}{P(X)} \quad \textit{Equation 2-7}$$

where $P(Y/X)$ stands for the conditional probability of Y given X.

This theorem can be derived from the conditional probability equation (Stuart & Ord, 1994).

Then replaced the express of $P(X)$ with total probability, we got the following formula:

$$P(Y_y/X) = \frac{P(X/Y_y)P(Y_y)}{P(X)} = \frac{P(X/Y_y)P(Y_y)}{\sum_{y=1}^{n} P(X,Y_y)/P(Y_y)}$$ *Equation 2-8*

Both formulas in the preceding theorem are known as the Bayesian theorem because they were initially proposed by Thomas Bayes (published in 1763). The first formula allows us to compute $P(Y/X)$ if we know $P(X/Y)$, $P(Y)$, and $P(X)$, while the second formula allows us to compute $P(Y_y/X)$ if we know $P(X/Y_y)$and $P(Y_y)$ for $1 \leq y \leq n$. Using either of these formulas, computing a conditional probability is known as Bayesian inference (Neapolitan, 2004).

2.2. Bayesian Network Theory

This section reviews the Bayesian Network (BN), a graphical model that represents probabilistic relationships between antecedents and consequents. BN is used for probabilistic inferences. The Bayesian theorem is simple when only two variables are included in the model. It becomes more sophisticated when more variables are involved (Neapolitan, 2004).

2.2.1. Bayesian Network Structure

The BN structure can be shown as a causal graph that must be directed and acyclic. This graph model, named Directed Acyclic Graph (DAG), is defined by a set of nodes and directed arrows. The nodes represent variables within the system of interest. Arrows symbolize dependencies or cause-effect relationships among nodes. Thus, the DAG is a graph of the preceding-consequent model.

Figure 2-1 is an example of the BN model. Nodes *Y* and *Z* are both antecedents of node *X*. Both *Y* and *Z* are also parents of X due to the direct arrows in this model.

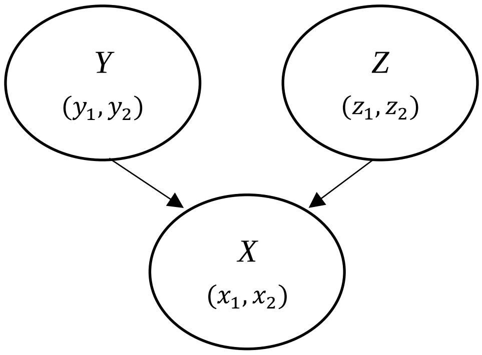


Figure 2-1. An example of a BN model

2.2.2. Bayesian Network Parameter

A parameter is the quantitative part of a network. The parameter of BN varies in conditional probability and marginal probability. The Conditional Probability Distribution (CPD) is often demonstrated as the Conditional Probability Table (CPT) (see Table 2-1). It represents the probability distribution of the node given the combinations of the parents' status. The marginal probability distributions should be used for the root node without any antecedent node.

Referring to the example model in Figure 2-1, let's assume nodes *X*, *Y &Z* are all binary with two possible status only. Then the CPT of node *X*, shown in Table 2-1, is the parameter of node *X*.

Table 2-1. CPT of node X in the example model

Status of node Y	Status of node Z	Degree of belief for child node *X* given the status of parents	
		x_1	x_2
y_1	z_1	$P(x_1/y_1, z_1)$	$P(x_2/y_1, z_1) = 1 - P(x_1/y_1, z_1)$
y_2	z_1	$P(x_1/y_2, z_1)$	$P(x_2/y_2, z_1) = 1 - P(x_1/y_2, z_1)$
y_1	z_2	$P(x_1/y_1, z_2)$	$P(x_2/y_1, z_2) = 1 - P(x_1/y_1, z_2)$
y_2	z_2	$P(x_1/y_2, z_2)$	$P(x_2/y_2, z_2) = 1 - P(x_1/y_2, z_2)$

For node *Y*, a Marginal Probability Table (MPT) is used to show its parameters (see Table 2-2).

Table 2-2. MPT of node Y in example mode

Status of node Y	y_1	y_2
Degree of belief	$P(y_1)$	$P(y_2) = 1 - P(y_1)$

Likewise, the MPT of node Z is the parameter.

Table 2-3. MPT of node Z in example mode

Status of node Z	z_1	z_2
Degree of belief	$P(z_1)$	$P(z_2) = 1 - P(z_1)$

Together, Figure 2-1 shows the combination of parameters as shown in Tables 2-1 – 2-3, forming a BN model.

A BN is a DAG with associated conditional probability distributions (Koski and Noble, 2009).

2.2.3. Bayesian Network Inference

A BN model allows for updating the degrees of belief to assign nodes, given a certain status of one or several variables as input. This update process is known as BN inference.

Taking the model in Figure 2-1 as an example, according to the law of total probability, the belief for $X = x_1$ could be calculated as follows:

$$P(x_1) = \sum_{i=1,2} P(x_1, y_i, z_i) = P(x_1/y_1, z_1)P(y_1)P(z_1) + P(x_1/y_2, z_1)P(y_2)P(z_1) + P(x_1/y_1, z_2)P(y_1)P(z_2) + P(x_1/y_2, z_2)P(y_2)P(z_2) \quad \text{Equation 2-9}$$

In which $P(x_1, y_i, z_i)$ is the joint probability that $X = x_1$, $Y = y_i$ and $\mathrm{Z} = \mathrm{z_I}$ occur.

$P(x_1)$, together with $P(x_2) = 1 - P(x_1)$ is a prior probability for node $X(x_1, x_2)$.

If there is an input of $Y = y_1$, which means $P(y_1) = 1$ and $P(y_2) = 0$, then $P(x_1)$ will be replaced by $P(x_1/y_1)$, and the degrees of belief will update as following

$$P(x_1/y_1) = P(x_1, y_1)/P(y_1) = P(x_1/y_1, z_1)P(z_1) + P(x_1/y_1, z_2)P(z_2) \quad \textit{Equation 2-10}$$

This process is shown in the probability table.

When the parameters in Table 2-1, Table 2-2 and Table 2-3 are specified, prior probabilities can be calculated following equations 2-5. Detail calculation is skipped, but the result of $P(x_i, y_i, z_i)$ is shown in Table 2-4.

Table 2-4. Probability table of $P(x_i, y_i, z_i)$ *in the example model*

Status of node Y	Status of node Z	Status of node X	$P(x_i, y_i, z_i)$
y_1	z_1	x_1	0.03
y_2	z_1	x_1	0.05
y_1	z_2	x_1	0.08
y_2	z_2	x_1	0.12
y_1	z_1	x_2	0.15
y_2	z_1	x_2	0.17
y_1	z_2	x_2	0.19
y_2	z_2	x_2	0.21

Note: $\sum_{i=1,2} P(x_i, y_i, z_i) = 1$

According to this table, Equation 2-9 equals:

$$P(x_1) = \sum_{i=1,2} P(x_1, y_i, z_i) = 0.03 + 0.05 + 0.08 + 0.12 = 0.28$$

This is the prior probability for node *X*. Given the input of $Y = y_1$, meaning $P(y_1) = 1$, according to equation 2-10, the posterior probability should be:

$$P(x_1/y_1) = P(x_1, y_1)/P(y_1) = (0.03 + 0.08)/(0.03 + 0.08 + 0.15 + 0.19) = \frac{11}{45} \approx 0.24$$

If the input is given as $X = x_1$, the belief for nodes *Y* and *Z* can also be updated following the same steps.

2.3. Procedure for Building a BN Model

The BN modelling procedure is essential to achieve robustness in data analysis. Building a BN model involves three primary steps (Darwiche, 2009). The first step is to decide on the set of variables and their possible values which will be represented as nodes. The second step is to build the network structure by connecting the variables into a DAG. The last step is to define the CPT for each network variable (node).

2.3.1. Discovering Nodes

In uncertain domains, human experiences and judgements are helpful, but they are often insufficient to make the best decision. It requires more sophisticated calculations, such as mechanical analysis of a machine, statistical analysis of traffic accidents, and pathology knowledge of diseases. As BN modelling reveals the conditional probability for a set of random variables and the causal probability relationships between variables, inferences based on the BN model can be used to aid in decision-making.

Nodes are essential elements of a BN model. There are multiple ways to define nodes, including identifying relevant contributors in the dataset, using expert judgement, learning from previous accidents, or using the combination of these methods. In addition, discovering nodes involves tagging the content with specific and practical taxonomy terms. However, as reviewed in Chapter 1, taxonomies varied across existing studies on human reliability analysis. For example, failures of the 'hardware system' can only be attributed to mechanical issues, such as mislocution or malfunction of a particular part, but systems involving more human factors can be more complex.

2.3.2. Building BN Structure

The network structure is essential for the BN model. It comprises a set of dependency links, representing causal relationships in the system. Expert judgement and mathematical analysis are the two most popular methods to determine the structure.

2.3.2.1. Expert Judgement

Expert judgement refers to the specification of the BN structure by humans. Although there is no restriction on the minimum number of experts, the judgement of multiple experts shows less subjectivity. Questionnaires are often used to collect expert judgement data.

Expert judgement is usually reliable when dealing with the ‘hardware system’ because parts of this type of system have clear and predefined relationships. Experts often show more agreement on the BN structure of the ‘hardware system’ than the ‘software system’ and the ‘combined system’ (Constantinou, Fenton and Neil, 2016). Therefore, expert judgement is widely adopted to define dependence relationships of the ‘hardware system’.

2.3.2.2. Mathematical Analysis

Mathematical analysis is believed to be more objective than expert judgement. Two approaches are used to learn the graphical structure in the data using mathematical analysis. The first approach is based on a constraint-based search (Verma, 1995). The second approach is a Bayesian search for graphs with the highest posterior probability given the data (Cooper Gfc, 1992; Spirtes & Scheines, 1993). In the case of different variable types, Richard E. Neapolitan recommended some methodologies (Neapolitan, 2004). Commercial software also provides algorithms to develop the BN structure. (Bayes server, 2019; BayesFusion, 2019; Murphy, 2003). We may choose different algorithms for different fields, but the issue is not just about selecting algorithms but the lack of sufficient data in some fields for mathematical analysis.

2.3.2.3. Hybridized Method

The hybridized method refers to the combination of the two methods mentioned above to minimize subjectivity and lower the standards for data quality. The order should be decided by the degree of liability in the target field. In the first approach, the BN structure is determined using an algorithm and then modified by expert judgement. In the second approach, the BN structure is first determined by expert judgement and then revised by an algorithm. An independent test, such as Pearson's chi-square test, is usually required for the second approach. This test examines the independence between two categorical variables and can be used as a complement method to expert judgement. It can also be used for preliminary data analysis in some structure learning algorithms (Tang & Srihari, 2012) or as a structure learning algorithm in some subjects with simple structures. Specifically, the Chi-square test, specified as the χ^2 test, is a goodness-of-fit test in which the model from the data is compared with a model based on the null hypothesis of independence (Hand, Mannila, & Smyth, 2001). Let X and Y be two multinomial variables governed by the distributions $P(X=x_i)$ and $P(Y=y_j)$. $O[x_i , y_j]$ is the count observed for each joint assignment of $X = x_i$ and $Y = y_j$. Given the null hypothesis that X and Y are independent, the expected count for (x_i, y_j) is $E[x_i, y_j]$. Then the χ^2 statistic (Wasserman 2004) for the data set (x,y) is defined by

$$\chi^2(x,y) = \sum\nolimits_{i,j} \frac{\left(O[x_i, y_j] - E[x_i, y_j]\right)^2}{E[x_i, y_j]}$$

The value of χ^2 is used to evaluate how likely the null hypothesis is true based on the observed count in a Chi-square distribution (Mood, Graybill, & Boes, 1974). The smaller the value, the more likely the variables are independent. The Chi-square distribution has been reported in previous studies (NIST/SEMATECH, 2012). Table 2-5 shows critical values for binary variables. However, there is no consensus on the cut-off value to categorize dependence and independence, but it calls for human judgement.

Table 2-5. Critical values for Chi-square distribution of binary variables

Dependence probability	0.5	0.75	0.90	0.95	0.975	0.99	0.999
Critical value	0.455	1.323	2.706	3.841	5.024	6.635	10.828

2.3.3. Developing CPT for a BN Model

There are two approaches to develop CPT in BN. One way is to learn distributions using data based on mathematical principles. The other way is to use expert judgement when the data is insufficient.

Neapolitan (2004) introduced the mathematical principles for parameter learning using data with different qualities. Several algorithms are used for parameter learning, such as the Maximum Likelihood Approach and the Bayesian Approach (Darwiche, 2009), which can also be used to deal with missing data (Blanco, 2005). However, the conditional probabilities may differ (even contradict) from one expert to another due to the influence of subjectivity. Jensen and Nielsen (2007) provided suggestions to minimize the adverse effects of subjectivity, such as taking the mean of the numbers or calculating a weighted average.

Data size is the main factor that should be considered when determining whether to use parameter learning or expert judgement. However, there is no strict cut-off value for the data size required to perform BN parameter learning. BayesFusion (2019) suggested that data cases should be at least ten times the number of nodes. Otherwise, the dataset cannot support parameter learning. However, it seems that the size of CPT also plays an important role. The size of CPT is the number of rows, which stands for the size of the combination for the circumstance. The reason is due to a common feature in the learning process. Even if there are ten times the number of data cases according to the scale of nodes, there may be some unavailable value in the CPT tables, which means there are no available data given the combination of parents' states. Table 2-6 shows an example of this circumstance.

Table 2-6. An example case of an unavailable value in CPT

Status of node Y	Status of node Z	Degree of belief for child node X given the status of parents	
		x_1	x_1
y_1	z_1	100%	0
y_2	z_1	90%	10%
y_1	z_2	unavailable	unavailable
y_2	z_2	1%	99%

There is an unavailable value because the dataset has not covered the specific circumstance of (y_1, z_2). Therefore, we need a prior parameter, known as the initial parameter. There were several methods to identify the initial parameter (Xiao et al. 2019; Nguyen, 2018; Steck, 2008). As for the binary node, an arbitrary number given by estimation or assumption is more efficient. Uniform distribution or random distribution are typical solutions in this subject.

2.4. Model Validation

The validity of a BN model is evaluated on the basis of the network structure and parameters. To validate the structure, we need to cross-check each dependency link by referring to results of mathematical analysis or our empirical knowledge and expertise. If the structure is discovered using the mathematical analysis, empirical knowledge, like expert knowledge, logical judgement, or even common sense, should be used for model validation. By contrast, mathematical analysis should be used for model validation if the BN structure is identified using expert judgement, in which the validation remains efficient even if the dataset only represents part of the structure. In particular, the amount of data should be sufficient and representative regardless of whether the dataset covers part or the whole BN structure. For the model parameters, they do not have to be precise, but they should represent how the system works. In other words, with a sensible network structure, the parameters will reveal the disparity of nodes and links.

There are a few methods that are often used to validate BN models. For example, the goodness-of-fit test is the method that is usually used to validate the structure and parameters of the BN model simultaneously. However, this test requires a large amount of data. It is not ideal for validating models containing nodes with discrete distribution of states, such as binary nodes. The what-if test examines whether a model works as it should by checking different consequences given different (opposite to binary nodes) probabilities. On the one hand, a different state of a virtual node, which can be judged by common sense, is supposed to lead to entirely different outputs. On the other hand, the analysis of an irrelevant node (relatively speaking) could be compared with the essential one to see if its influences significantly differ. For this purpose, several typical nodes should be chosen and performed on what-if analysis individually. Due to the limitation of expert judgement and insufficient available data, the assessment model is not expected to be accurate but reveals the causal links between contributors and consequences within complex systems. Instead, the most important contributors and links are expected to be located.

2.5. Inference Analysis with the Bayesian Network

After calculating the probabilities of the variables, inference analysis is performed to find the most important contributors, as shown in Section 2.2.3. There are two types of inference analysis: predictive analysis and diagnostic analysis depending on the direction of arrows in the BN model. Note that as the BN models that can be applied to most systems are more complex than the one shown in Figure 2-1, specific algorithms must be applied to the inference process, such as Pearl's message passing algorithm, the junction tree algorithm, the symbolic probabilistic inference algorithm, the logic sampling algorithm, the likelihood weighting algorithm, and Cooper's best-first search algorithm (LI et al. 2008; Nagarajan, Scutari, & Lèbre, 2013; Neapolitan, 2004).

2.5.1. Predictive Analysis

Predictive analysis aims to find the most probable consequence initiated by a specific state of one or more nodes. In this inference process, the node representing the event that occurred, as input information to the model, is the ancestor of the assigned node or nodes within the BN graph. The inference example from node Y to node X in Section 2.2.3 follows this sequence.

2.5.2. Diagnostic Analysis

Diagnostic analysis explores the most probable contributor that leads to an event. Here, the node standing for the event is a descendant of the assigned node or nodes within the BN. For example, diagnostic inference is to update the belief of Y and Z given $X = x_1$ in the model presented in Section 2.2.

Chapter 3. Modelling for a Human Performance Separated System Based on Expert Judgement and Human Perception Influence Analysis

This chapter reports on the procedure for building a Bayesian network (BN) model for assessing the failure of the Human Performance Separated System (HPSS). This chapter aims to demonstrate how a BN model can be applied to a hardware system that operates automatically and only requires minimum inputs from human, such as “start” and “stop”. By contrast, the Human Performance Included System (HPIS) involves not only the hardware, but also complex variables such as human factors. Compared with HPIS, modelling the failure of HPSS is more straightforward, since the links between contributors are clear-cut and are usually specified during the design.

First, the procedure for developing a BN model to assess HPSS failure is reported. This modelling procedure was conducted using BN based on expert judgement, since lack of data is still the main problem in many industrial sectors. Then, the principles and key points of the modelling procedure are reported. Finally, a method is proposed to examine the influence of human perception on the performance of the BN model as an example of a human reliability analysis (HRA). Our modelling process combines expert judgement with numerical analysis and reveals the importance of factors by calculating their probabilities. When there are sufficient data, it is possible to replace expert judgement by mathematical analysis, at least part of it. Compared to traditional failure models, the BN model can show clearer dependence between contributors and can be generalized to different industrial sectors.

3.1. Procedure for Developing an HPSS Failure Assessment Model with Bayesian Network

An HPSS includes multiple mechanical components or system functions. It is often straightforward to find out how an HPSS works because the functions of its components or parts and the dependencies between them are specified when the system is designed. Thus, even with insufficient data, expert-informed mechanical reasoning is a reliable method for developing the network structure.

3.1.1. Finding Nodes

Experts in the relevant field are often asked to find nodes for the mechanical features or relations of an HPSS. In general, there are four steps to complete this task.

1) Find a suitable node classification scheme, such as similarity of functions or features of the system. Expert knowledge in a specific field is required.

2) Read accident investigation reports to find and classify causations of accidents. Expert consensus is required.

3) Define each node. Expert knowledge in a specific field is required.

4) Define the state, i.e., the type and size, of nodes. The type of nodes can be discrete or continuous. Expert judgement is required to make this decision. Nevertheless, to simplify the calculation process, the type of nodes of a mechanical system can be defined as a discrete variable. Although evaluation of mechanical equipment is usually required to define the size of the nodes, the size of the nodes can be defined as a binary variable in the BN model to reduce the workload of parameter learning. In addition, the system's operation can be defined on the basis of whether it operates regularly or irregularly (sometimes it is defined as normal or abnormal).

3.1.2. Procedure for Building Dependency Arrows

To build dependency arrows, we should go through accident investigation reports and use expert judgement to find the failure path. Steps to build dependency arrows are shown below:

I. Build an initial antecedent-consequent group model based on expert knowledge to represent the hierarchy of the groups.

II. Find all possible dependencies between two given nodes. This step can be done in three sub-steps:

1) Check each pair of nodes from a different hierarchy level, one from the antecedent group and the other from the consequent one.
2) Check each pair of nodes within the same group.
3) Check each pair of nodes from the same level of groups (if they have) which have no antecedent-consequent relations.

Sometimes there might be some unclear links, which can be classified into direct and indirect connections. The direct link means that a causal relation is evident, while the indirect link does not show a clear causal relation.

III. Build a dependency chain for each indirect link. For example, there is no direct dependency between A and C, but A may influence C through B, then we have A→B→C.

IV. Cross-check direct link and indirect link. Every link in the dependency chain should correspond to a direct link, i.e., A→B and B→C should both exist.

3.1.3. Key Points of Building Dependency Arrows

To build dependency arrows, one shall pay attention to three key points:

First, follow the hierarchy rule. The dependency arrow should start from the node within the antecedent group and point to another within the consequent group. The dependency arrow can also be placed between nodes within the same level group. This is not a strict rule, but it helps reduce the occurrence of cyclic relations.

Second, avoid reciprocal links. Only one arrow is allowed to go in one direction between two given nodes. This is a principle that cannot be violated. However, components might mutually influence each other in some situations. To deal with such problems, four solutions can be applied, as shown below:

Given a dependency chain as (A←→B) →C, in which A and B are mutually linked:

I. The node within the reciprocal links could be split. Node A could be divided into A1 & A2 due to different mechanical reasons, functions, or locations. Then node A1 becomes the cause of node B, while A2 could be considered a consequence.

A1→B→C

B→A2→C

II. The nodes are independent, indicating that they can lead to consequences separately. In other words, each node that fails can cause a consequence. For this instance, we delete the links between the nodes, and then the probability equation became as follows:

A→~~B~~→C

B→~~A~~→C

$P(C_i)=P(C_i /A)P(A) \cup P(C_i /B)P(B)$

III. One node dominates the other. The chance that the domination node causes the other is much higher than the reverse situation. This could be considered an antecedent-consequent dependency, so we can only keep the link from antecedent to consequent and delete the reverse one. The demonstration and probability equation is shown below:

A→B→C

~~B→A→C~~

$P(C_i)=P(C_i /B)\, P(B/A)\, P(A)$

IV. The two nodes within the reciprocal links must fail to cause other consequences, and the chance of causing the other consequence is approximately equal. In this situation, we can introduce a joint node to replace them; then, the probability equation becomes as follows:

Joint nodes (AB)→C

$$P(C_i)=P(C_i /AB)\ P(AB)=P(C_i /AB)\ P(A)\ P(B)$$

Third, build a direct acyclic graph (DAG), in other words, to avoid any cyclic link.

Although the reciprocal link is a type of cyclic link, another typical cyclic relationship is a cyclic chain, such as A→B→C→A. There are two ways to cope with this cyclic chain:

I. Some link within this chain is weak and could be deleted. For instance,

A→B, ~~B→C~~, C→A

II. The node within the chain could be split. For instance,

A1→B→C→A2

or

A→B→C1 & C2→A

3.1.4. Developing Model Parameters using Human Perception

In the present study, the term human perception stands for expert judgement about the conditional probability distribution of each node within the BN model. With insufficient data, human perception becomes the only option to develop model parameters, which means that we fill in the probability table using expert opinions. The challenge is the size of the Conditional Probability Table (CPT), which expands exponentially as the number of parents of a child node increase. For example, if a child node has three parents with binary states, there are 8 (2^3) combinations of the parent state. When the node has four binary parents, there will be 16 (2^4) combinations and 32 (2^5) varieties for the node with five parents. When the size of CPT is too big, it is impractical and unreliable to use human perception. Ideally, the number of parents for each node should be no more than three. The idea to fix the problem is to narrow the size of each CPT by introducing intermedia node(s) between the child node and some of its parents. The procedure is as follows:

I. Check with all parents of this kind of child node and find out if there are any common features of the link, such as similar function, mechanics or influence route.

II. Introduce an intermedia node between the route to link these parents and the corresponding child. It should be noted that the same gathering of parents leading to the different children must not share the same intermedia node.

To fill the CPT, we shall follow the principles below:

I. For the parent node, expert opinions can decide which parent node has a more significant influence than other parent nodes. For example, A and B are both parents of C. If A's failure is much more likely to affect C than B to affect C, then the failure probability number of C only given that A failed should be much bigger than only given that B failed.
II. For a root node without any antecedent, the CPT is replaced by a MPT, representing the event occurring unconditioned on any other event and thus forms a powerful statement.
III. For an intermedia node, if the states of gathering parents are the same, this intermedia node could be in the same condition; in other words, the probability of this state is 100%. Otherwise, the states should be 0%.
IV. 100% or 0% should only be filled in when the result is unquestionable and without any exception.
V. If there is very little chance of causing a result, we could choose a small number like 0.1%.

3.2. Influence of Human Perception on Model Performance

Model performance refers to the output represented by the marginal probability distribution of the designated node. Since expert opinions may differ from one person to another or even the same expert may provide different opinions at different times, it is important to know how human perception influences model performance. To answer this question, the sensitivity of the conditional probability distribution is calculated, representing the strength of the dependency link. This could be analysed using two methods: correlation coefficient and sensitivity analysis. A correlation coefficient is a numerical measure that represents the statistical relationship between two variables. Sensitivity analysis studies how the uncertainty in the output can be divided and assigned to different sources of uncertainty in its inputs.

3.2.1. Correlation Between Human Perception and Model Output

The correlation coefficient indicates the relationship between human perception and model output, whether positive or negative, strong or weak. The Karl-Pearson correlation coefficient formula is a common method used to calculate this.

$$\rho_{xy} = \frac{cov(XY)}{\sigma_x \sigma_y} \qquad \text{Equation 3-1}$$

where:

X is a variable for human perception

Y is a variable for the model output corresponding to X

ρ_{xy} is the correlation coefficient o(X, Y)

cov is the covariance

σ_x is the standard deviation of X

σ_y is the standard deviation of Y

The human perception value could be a continuous or discrete variable based on human perception. With countable guesses, a perception sample can be developed, and the equation can be transformed as follows:

$$r_{xy} = \frac{\sum_1^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_1^n (x_i - \bar{x})^2}\sqrt{\sum_1^n (y_i - \bar{y})^2}} \qquad \text{Equation 3-2}$$

where:

x is a variable for human perception in a sample

y is a variable for model output in the sample

r_{xy} is the correlation coefficient of (x, y)

n is the sample size

$\bar{x}$ is the sample mean $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$; and analogously for $\bar{y}$

The correlation coefficient falls between [−1, +1]. Positive value stands for positive relationship, while negative value stands for negative relationship association. An absolute value closer to 1 means a more substantial relation, while closer to 0 means a weaker link.

3.2.2. Sensitivity Analysis for Human Perception

Sensitivity analysis explores the division of the uncertainty in the model output by manipulating the perception. The idea is to change the perception, to see which one impacts the output. We shall manipulate one input variable while keeping other variables at baseline values to calculate the sensitivity coefficient. The sensitivity coefficient is defined below:

$$Sensitivity\ Coefficient = \frac{\Delta output/output\ baseline}{\Delta perception/perception\ baseline} \quad \text{Equation 3-3}$$

where:

$\Delta perception$ is the difference between changed perception and its baseline

$\Delta output$ is the difference between changed output and baseline

A more significant value of the sensitivity coefficient means a higher sensitivity to the output using human perception.

Chapter 4. Assessment Model for Gas Turbine Failures and Human Perception Influence Analysis

This chapter demonstrates how the procedure and principles of building an BN model for the HPSS can be applied in real-world situations using the gas turbine failure as an example. The first part of this chapter reports on the building of a BN model for gas turbine failure. This model is used as an example to demonstrate how to build a BN model using expert judgement. The second part of this chapter presents a validation of the BN model using hypothesized cases of gas turbine failure. The third part of this chapter reports the influence of human perception on model performance.

4.1. Procedure for Developing the Model

4.1.1. Nodes of the BN Model for Gas Turbine Failure

Contributors related to gas turbine failure have been discovered using expert knowledge. There are thirty-one contributors in six groups (see Table 4-1).

Table 4-2 shows the nodes with the definitions used in the gas turbine model. Not all factors were used in the gas turbine model. The underlined factors (F1, F2, E1, E2, E3, B7, B8, B9) were not temporarily adapted to the model, and the italicized factors (B6 & B10) were divided according to the acyclic rule.

4.1.2. Finding Dependencies between Nodes

This step aims to find the mechanical relationships between nodes using expert knowledge.

Table 4-1. Contributors related to gas turbine failure

Operative type		Maintenance type		Main components		Core components		Cause of failure		System function	
Node	Contributor	Node	Contributor	Node	Contributor	Node	Contributor	Node	Contributor	Node	Contributor
F1	Baseload	E1	Preventive maintenance	D1	Rotor	C1	Compressor blading	B1	Over-Speed	A1	Fuel system
F2	Variable load	E2	Predictive maintenance	D2	Compressor	C2	Combustor	B2	Sealing rupture	A2	Lube oil system
		E3	Corrective maintenance	D3	Combustion chamber	C3	Turbine blading	B3	Blading rupture	A3	Hydraulic/pneumatic control system
				D4	Turbine	C4	Bearing	B4	TBC spallation	A4	Digital Control System
						C5	AC pump	B5	Misalignment	A5	Secondary air-cooling system
						C6	Emergency pump	*B6*	*Overheating*	A6	Uninterruptible power supply
								B7	Foreign object		
								B8	Design / manufacturer / assembly failure		
								B9	Unexpected cause		
								B10	*Vibration*		

Table 4-2. Nodes used in the gas turbine model

Group	Node	Contributor	Definition
Function system	A1	Fuel system	Fuel transfer gate, dual fuel (oil and gas) application, power augmentation, emission control, piping, fuel control line, filter, control and safety valves, ventilation valves
	A2	Lube oil system	Tank, piping, filter, valves, interface pumps (AC, DC, Jacking), control system
	A3	Hydraulic/pneumatic control system	Piping, valves (solenoid)
	A4	Digital control system (DCS)	All lines for safety and control functions between DCS and actuators
	A5	Secondary air-cooling system	Internal and external cooling, rotor and blade cooling, film cooling, etc.
	A6	Uninterruptible Power Supply (UPS)	Infrastructure of battery operation and emergency diesel
Failure cause	B1	Over-speed	All influences causing an uncontrolled overspeed event, especially those introduced by malfunctions of the fuel system or the control system
	B2	Sealing rupture	Ruptures at the rotor and/or stator
	B3	Blading rupture	Ruptures in the compressor or turbine
	B4	TBC spallation	Spallation at rotating or stationary parts, e.g., blades, vanes, or combustion chamber
	B5	Misalignment	Wrong fit components through failure in design or manufacturing as well as assembly
	B6T	Thermal overheating	Caused by a failure in the combustion system affecting all components in the hot gas path
	B6M	Mechanical overheating	Caused by mechanical contact due to mismatching of parts
	B10T	Thermal vibration	Resonance in the combustion system, causing mechanical damage
	B10M	Mechanical vibration	Unbalance caused by the liberation of parts or misalignment
Core components	C1	Compressor blading	Compressor blade component
	C2	Combustor	Single fuel and dual fuel application
	C3	Turbine blading	Turbine blade component
	C4	Bearing	Journal bearings and axial pads to control the rotor
	C5	AC pump	Main pump with piping
	C6	Emergency pump	DC pump (emergency pump with piping) and jacking pump (lifting pump with piping)
Main components	D1	Rotor	All rotating parts like discs or shaft segments, including compressor and turbine blades, as well as sealing

	D2	Compressor	Rotor, compressor casing, and blading
	D3	Combustion chamber	Cooling path, heat shields, and transition pieces
	D4	Turbine	Rotor, turbine casing, and blading

4.1.2.1. Hierarchy of groups

To find the dependencies, the first step is to define the hierarchy of groups. Figure 4-1 shows the initial antecedent-consequent group model.

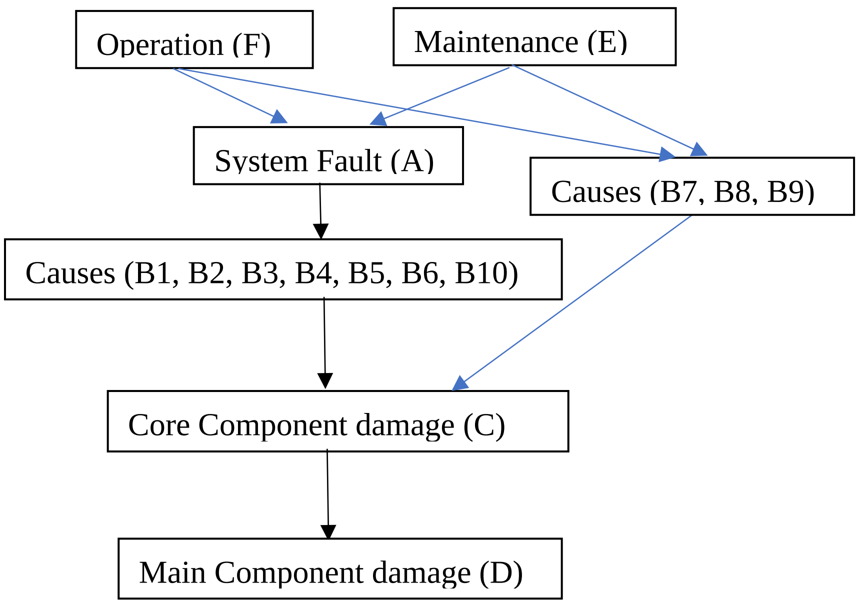


Figure 4-1. Hierarchy of groups within a gas turbine model

Since 'Operation' & 'Maintenance' are the primary processes in gas turbine technology, their status can be identified by analysing specific mechanical equipment. To simplify the model, it was assumed that the system was in preventive maintenance at base load, so Groups E & F (as shown in Table 4-1) were removed. Since the model aimed to trace system failures only during the working stage, failures related to design, manufacturing, and assembly were ignored. In addition, 'foreign objects' and 'unexpected causes' were not considered. Therefore, nodes B7, B8 and B9 (as shown in Table 4-1) were removed. All nodes used in the gas turbine model are shown in Table 4-2.

4.1.2.2. Dependency Table

All dependency relationships were established by expert judgement. Dependency tables can be categorized into three types depending on the groups or node pairs. For example, failure of compressor blade (C1) and bearing (C4) may affect compressor behaviour (D2). The compressor blading (C1) and bearing (C4) are the parents. Each pair of nodes can either have a direct or indirect link in the dependency table. A direct link refers to a clear causal relation between nodes, while an indirect link indicates a vague relation between nodes. A link chain was developed to show the dependency of indirect links.

1) Dependencies between nodes of different groups
   - Group C and Group D
   - Group B and Group C
   - Group A and Group C
   - Group A and Group B

These groups contain both direct and indirect dependencies. The indirect dependencies, such as the cyclic interdependencies, were complex and were not allowed in the BN model. In some cases, interdependencies can be considered as contributors of minor importance. Taking them out would not change the model significantly, as shown in Section 3.1.3. Node 'overheating (B6)' was split into two nodes, known as 'thermal overheating (B6T)' and 'mechanical overheating (B6M)' (see Table 4-2). For the same reason, the node 'vibration (B10)' has divided into 'thermal vibration (B10T)' and 'mechanical vibration (B10M)' (see Table 4-2). More details can be found in Part I of Appendix A.

2) Dependencies between nodes of the same group
   - Within-group C
   - Within-group B
   - Within-group A

3) Emergency system
   - Uninterrupted Power Supply (A6)

- Thermal acoustic induced vibration (B10T)
- Mechanical vibration (B10M)
- Over-speed (B1)

Table 4-3. Dependency table for the child-parent links

No.	Child	Parent					
1	A1	A3					
2	A2	C5	C6				
3	A3	A4					
4	A4	n.a.					
5	A5	n.a.					
6	A6	n.a.					
7	B1	A1	A4				
8	*B2*	B1	B5	B6T	C4		
9	*B3*	B1	B5	B6T	C4		
10	B4	B6T					
11	B5	A4	B6T	C4			
12	B6T	A1	A5				
13	*B6M*	B2	B3	B5	C4		
14	B10T	A1	A4				
15	B10M	A4	B1	B3			
16	*C1*	B1	B6M	B10M	C4		
17	C2	B1	B4	B10T			
18	*C3*	B1	B4	B6M	B10M	C2	C4
19	*C4*	A2	B1				
20	C5	n.a.					
21	C6	A4	A6				
22	D1	C1	C3	C4			
23	D2	C1	C4				
24	D3	C1	C2				
25	D4	C1	C2	C3	C4		

In this model, four emergency systems were extracted one by one. As these systems only operate in emergency situations and cause no damage when they are not in operation, they are controlled as fail-safe systems. As emergency systems work only when a specific value has surpassed the limit, two dependency chains are included. These dependency chains can be converted to a child-parent dependency table (see Table 4-3). See Part II of Appendix A for all eleven dependency tables.

4.1.3. Network Structure for the Causation of Gas Turbine Failure

To define the network structure of gas turbine failure, we must draw a graph with nodes and dependency arrows between them based on Table 4-3. Figure 4-2 shows the structure graph revealing contributors to a gas turbine failure. For instance, D2 has two parents, known as C1 and C4. Therefore, two separate arrows start from C1 and C4, and both point to D2.

4.1.4. Developing Conditional Probability Tables

Expert judgement is used to develop the Conditional Probability Table (CPT) for each node with two possible states (regular vs. irregular).

4.1.4.1. Intermedia Nodes

As mentioned in Section 3.1.4, intermedia nodes were introduced to deal with nodes with more than three parents. There are six nodes of this kind (B2, B3, B6M, C1, C3, and D4) (see Table 4-3). Figure 4-3 demonstrates how an intermedia node works. As compressor blading and turbine blading are both blading failures and their failures similarly affect the turbine, an intermedia node (ID4) is thus included between blading (C1, C3) and turbine (D4). All figures related to intermedia nodes can be found in Part II of Appendix A.

Figure 4-2. Structure of contributors to gas turbine failure

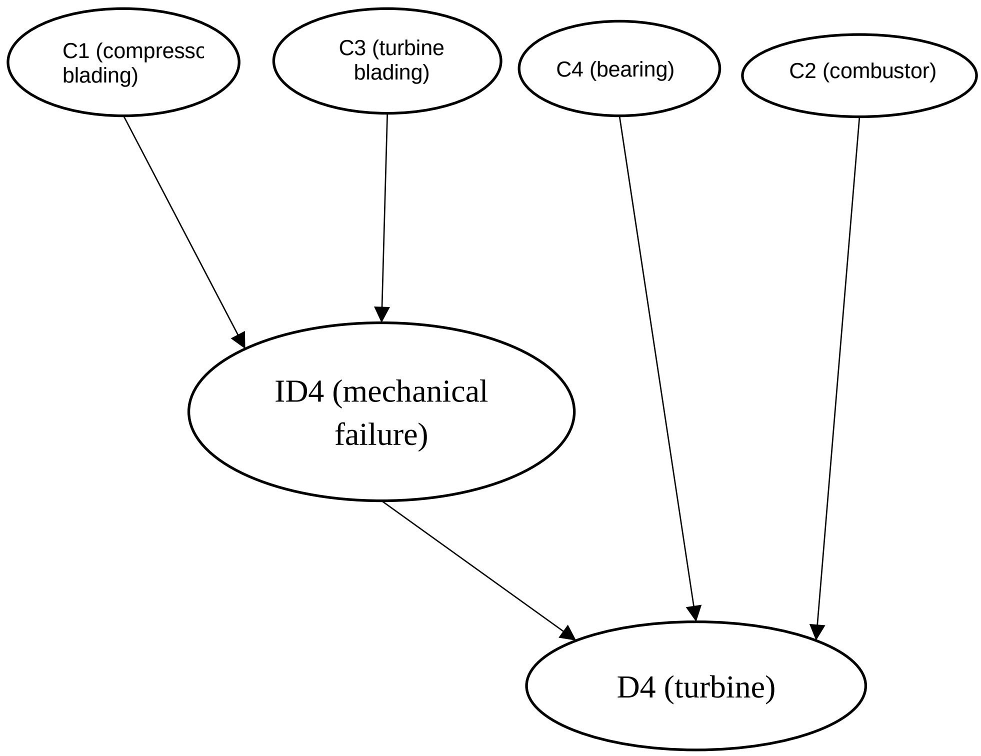


Figure 4-3. Intermedia node model of turbine

Seven intermedia nodes are required to deal with six child nodes (see Table 4-4). Figure 4-3 shows the rows related to D4 in Table 4-4.

Table 4-4. Dependency table for child-parent with intermedia nodes

Child	Parent			Mechanical translation of the intermedia node
B2	B1	B6T	<u>*IB2*</u>	
<u>*IB2*</u>	B5	C4		Mechanical operation failure
B3	B1	B6T	<u>*c*</u>	
<u>*IB3*</u>	B5	C4		Mechanical operation failure
B6M	C4	<u>*IB6M*</u>		
<u>*IB6M*</u>	B2	B3	B5	Mechanical operation failure
C1	B1	<u>*IC1*</u>		
<u>*IC1*</u>	B6M	B10M	C4	Mechanical operation failure
C3	B1	<u>*I1C3*</u>	<u>*I2C3*</u>	
<u>*I1C3*</u>	B6M	B10M	C4	Mechanical operation failure
<u>*I2C3*</u>	B4	C2		Hot gas path failure
D4	C2	C4	<u>*ID4*</u>	
<u>*ID4*</u>	C1	C3		Mechanical failure

4.1.4.2. Probability Table with Expert Judgement

In total, thirty-two CPT and four marginal probability tables are required for the BN model. Table 4-5 to Table 4-8 show examples of probability tables. The letter 'I' stands for irregular working state, while the letter 'R' stands for regular. Table 4-5 shows the probability of A1 (fuel system). If A3 ((hydraulic/ pneumatic control system) works irregularly, it is likely that A1 works irregularly. According to expert judgement, this probability is 80%. When A3 works regularly, the chance of an irregular state for A1 is very low. However, it is kept in the model for other reasons, such as human errors in the operation or maintenance of the fuel system, whose probability is around 1% based on expert judgement.

Table 4-5. Conditional probability of A1 (fuel system)

A3 (hydraulic/ pneumatic control system)	Probability of A1 (fuel system)	
	A1=I	A1=R
I	80%	20%
R	1%	99%

Table 4-6 shows the probability of A4 (digital control system). Since A4 is a root node in this model, the probability of A4 contains a marginal probability. The failure chance of a digital control system is rare due to its high technical standard. Thus, the probability is 0.1% based on expert judgement.

Table 4-6. Marginal probability of A4

Probability of A4 (digital control system)	
A4= I	A4=R
0.1%	99.9%

Table 4-7 shows the probability of B1 (over-speed) based on expert judgement. When both A1 and A4 work irregularly, the chance of overspeed is 99%. When A1 or A4 work irregularly, the chance of overspeed is 20% and 90%, respectively. When both A1 and A4 work regularly, the chance of overspeed is 0.1%.

Table 4-7. Conditional probability of B1 (overspeed)

A1 (fuel system)	A4 (digital control system)	Probability of B1 (overspeed)	
		B1=I	B1=R
I	I	99%	1%
R	I	90%	10%
I	R	20%	80%
R	R	0.1%	99.9%

Table 4-8 shows an example of the probability of C6 (emergency pump). A4 (digital control system) and A6 (UPS) conditions are the parents of C6. Once either parent has an irregular state, C6 cannot work regularly (100%). According to expert judgement, A4 and A6 work periodically, and thus the probability of a bearing problem is 0.1%.

Table 4-8. Conditional probability of C6 (Emergency pump)

Condition of A4 (Digital control system)	Condition of A6 (UPS)	Probability of C6 (Emergency pump)	
		C6=I	C6=R
I	I	100%	0
R	I	100%	0
I	R	100%	0
R	R	0.1%	99.9%

All conditional tables can be found in Part III of Appendix A.

4.2. Validation

A what-if analysis with hypothetical cases was performed to validate the model and a belief propagation algorithm was used that executed the BN inference process.

4.2.1. Emergency Pump Failure

Take an emergency pump failure as an example. Given a hypothetic input with an irregular emergency pump (C6=I), inferences could be made based on a diagnosis analysis and a prognosis analysis.

- Diagnosis analysis

A diagnostic analysis was first used to identify the contributors to the emergency pump failure. This analysis calculated the probability of parent or antecedent nodes contributing to the emergency pump failure by building a gas turbine model. According to Figure 4-2, A4 (Digital control system) and A6 (UPS) are the parents of C6 (emergency pump). The irregular probabilities of A4 and A6 are shown below:

① Irregular probability of A4 is 33.37%,

② Irregular probability of A6 is 33.37%.

The irregular probabilities of A4 and A6 are the same because they have identical marginal probability distribution (see marginal probabilities of A4 and A6 in Appendix A) and equal weights in the CPT table of C6 (see Table 4-8).

- Prognosis analysis

Then a prognostic analysis was conducted to estimate the consequences of an emergency pump failure. This process calculated the probability of the child or the descendant nodes that may contribute to the emergency pump failure. For example, as the child of C6, the irregular probability of A2 (lube oil system) is 0.1%. This value is small because either the parent of A2, speaking of C6 or C5 (AC pump) alone, can guarantee that A2 works regularly. In this case, the emergency pump failed (C6 = I) and there is no input from C5, whose irregular probability is 0.1%, without any input from the child or descendant node. However, the probability varies with different inputs. Table 4-9 shows the prognosis analysis of D1(rotor) with different combinations of inputs in an emergency pump failure.

The reference case refers to no input involved, and the default parameters are used for D1. In this case, the irregular probability of DCS (A4=I) is 0.1% by expert judgement (see Table 4-6). The irregular probability of D1 is 6.83%, which is the prognostic result in this case.

Table 4-9. Prognoses of the rotor based on emergency pump failure

Case No.	Input		Probability of irregular rotor (D1=I)
	1st input	2nd input	
Reference case	n/a	n/a	6.83%
Case 1	Emergency pump working irregularly (C6=I)	n/a	86.47%
Case 2		DCS working irregularly (A4=I)	99.59%
		DCS working regularly (A4=R)	6.26%
Case 3		UPS working regularly (A6=R)	92.32%
		UPS working irregularly (A6=I)	6.98%

Case 1 refers to one input that C6 (emergency pump) works irregularly. In this case, the irregular probability of D1 is 86.47%. This high value, which means a high failure probability, is linked with a 33.37% irregular probability of A4, an important component in the gas turbine. We introduce additional inputs to prove this, as shown in Cases 2 and 3.

In Case 2, there is an additional input of A4 (DCS) in addition to C6=I. If the evidence shows that DCS works irregularly (A4=I), the irregular probability of D1 is higher than in Case 1. Suppose the evidence shows that DCS works regularly (A4=R). In that case, the irregular probability of D1 is even lower than in the reference case (0.1%) because the irregular probability of A4 in the reference case is 0.1%, according to the marginal probability table of A4 (see Table 4-6).

Case 3 shows an additional input of A6 instead of A4. If the input shows UPS works regularly (A6=R), which also means the emergency pump failure (C6=I) is most probably caused by A4, then it raises the irregular probability of D1 (rotor). If the input shows that the UPS works irregularly (A6=I), the emergency pump failure (C6=I) is probably caused by A6. Since both A6 (UPS) and C6 (emergency pump) are components, they only work when the main ones fail. Therefore, in this case, the irregular probability of D1 only increases by an insignificant amount compared to the reference case.

4.2.2. TBC Spallation Failure

Take the TBC spallation failure (B4=I) as another example.

- Diagnosis analysis

The diagnosis analysis aims to calculate the probability of the parent or antecedent node of B4 (TBC spallation). According to Figure 4-2, B6T (thermal overheating) is a parent of B5. The analysis result shows that the irregular probability is 41.29%.

- Prognosis analysis

The prognosis analysis shows that the irregular probability of B6M (mechanical overheating) and D4 (turbine) are 74.32% and 98.53%, respectively. TBC spallation is associated with thermal problems, but the difference between the state of B6T (thermal overheating) and B6M (mechanical overheating) lies in the additional inputs. Table 4-10 shows the prognosis analysis of D4 according to B4 with more input.

Table 4-10 shows that both TBC spallation and the overheating problem play an important role in the probability of turbine failure. If there is no overheating problem, even when TBC spallation occurs, the irregular probability of turbine failure reduces to 10.55%. In contrast, if the overheating problem is not apparent, the irregular probability of the turbine is exceptionally high.

Table 4-10. Prognoses of the turbine based on TBC spallation

Case no.	Input		Irregular probability of turbine (D4=I)
	1st input	2nd input	
Reference case	n/a	n/a	9.03%
Case 1	TBC spallation (B5=I)	n/a	98.53%
Case 2		No thermal overheating (B6T) =R	72.32%
Case 3		No mechanical overheating (B6M) =R	80.31%
Case 4		No overheating issue (B6T, B6M) =R	10.55%

4.2.3. Thermal Overheating

The last example shows the influence of TBC spallation due to overheating. Then, let us look at another example of thermal overheating. The input is that the thermal overheating state is irregular (B6T=I).

- Diagnosis analysis

According to Figure 4-2, A1 (fuel system) and A5 (secondary air-cooling system) are the parents of B6T. The diagnostic results are:

① Irregular probability of fuel system (A1) is 84.65%,

② Irregular probability of a secondary air-cooling system (A5) is 7.37%.

Although A1 and A5 have equal weights in the conditional probability table of B6T (see conditional probability table of B6T in Appendix A), the irregular probability of A1 here is much higher than A5. This is because A1 has a higher chance of failure than A5, which can be found in the marginal probability tables of A1 and A5.

- Prognosis analysis

Table 4-11 shows the prognosis analysis of D4 (turbine) with additional inputs. The results show that the probability of an irregular turbine (D4) is 98.70%, given only the thermal overheating problem. Cases 2-6 indicate little change in the result given different additional inputs, which means that overheating is highly harmful to the turbine.

Table 4-11. Prognoses of the turbine based on thermal overheating

<table>
<tr><th rowspan="2"></th><th colspan="2">Input</th><th rowspan="2">Irregular probability of turbine (D4=I)</th></tr>
<tr><th>1st input</th><th>2nd input</th></tr>
<tr><td>Reference case</td><td>n/a</td><td>n/a</td><td>9.03%</td></tr>
<tr><td>Case 1</td><td rowspan="6">Thermal overheating occurs

(B6T=I)</td><td>n/a</td><td>98.70%</td></tr>
<tr><td>Case 2</td><td>Fuel system working regularly (A1=R)</td><td>95.28%</td></tr>
<tr><td>Case 3</td><td>Cooling system working regularly (A5=R)</td><td>98.83%</td></tr>
<tr><td>Case 4</td><td>No rupture (B2, B3) =R</td><td>89.91%</td></tr>
<tr><td>Case 5</td><td>No mechanical overheating (B6M=R)</td><td>91.71%</td></tr>
<tr><td>Case 6</td><td>No vibration (B10M, B10T=R)</td><td>97.14%</td></tr>
</table>

4.2.4. Mechanical Vibration

Mechanical vibration is another function failure case. Let's introduce the input in which the state of mechanical vibration is irregular (B10M=I).

- Diagnosis analysis

According to Figure 4-2, B3 (blading rupture) and A4 (DCS) are the parents of B10M. The diagnostic results are:

① Irregular probability of blading rupture (B3) is 93.31%,

② Irregular probability of DCS (A4) is 0.24%.

These results suggest a greater chance of mechanical vibration caused by blading rupture than DCS failure.

➢ Prognosis analysis

According to Figure 4-2, C1 (compressor blading) and C3 (turbine blading) are the children of B10M (mechanical vibration). D4 (turbine) is the descendent of B10M (mechanical vibration). See below for the prognostic results:

①Irregular probability of compressor blading (C1) is 0.7938

②Irregular probability of turbine blading (C3) is 0.8763

③Irregular probability of turbine (D4) is 0.9944

Then, let us introduce additional inputs (see Table 4-12). Only Case 5 shows a small value of the irregular probability of the turbine, suggesting that we should check compressor blading and turbine blading when mechanical vibration occurs. If both blading parts work regularly, it is likely that the turbine still works. Otherwise, the turbine probably does not work.

Table 4-12. Prognoses of the turbine based on mechanical vibration

	Input		irregular probability of turbine (D4 = I)
	1st input	2nd input	
Reference case	n/a	n/a	9.03%
Case 1	Mechanical vibration occurs (B10M = I)	n/a	99.44%
Case 2		No blading rupture (B3=R)	92.35%
Case 3		No compressor blade rupture (C1 =R)	90.92%
Case 4		The turbine blading works regularly (C3=R)	80.53%
Case 5		Both compressor and turbine blades work regularly. (C1, C3=R)	14.17%

4.2.5. Conclusion of the Validation

The results of these validation cases meet the logical reasoning, suggesting that the model allows us to analyse the gas turbine failure.

4.3. Analysis of Human Perception Influence

As the probability tables in the model were developed by expert judgement, human perception played a role there. Thus, it is important to examine the influence of human perception by performing a sensitivity analysis in which different values in the probability table were assigned and the corresponding results were compared. In this analysis, only the irregular probabilities of the target nodes were examined, while all parent nodes were assumed to work regularly.

4.3.1. Three Types of Irregular Probability with the Assumption of All Parents Working Regularly

Theoretically, each node can have a different probability. However, since these values are assigned by expert judgement, it may not be possible to give each node a unique value. Furthermore, as human perceptions are sometimes inaccurate, the benefit of using expert judgement is unclear. Thus, to be practical, the nodes were classified into three types depending on possible reasons that induce irregularity when all parent nodes work regularly, including operation error, material flaw, and other conditions.

- Type 1- Operation error

The irregular states of these nodes are most likely caused by an operation error, given that all parent nodes work regularly. The failure probabilities of these nodes are higher than those of others.

Table 4-13. Type 1 nodes for human perception analysis

Type 1 nodes	Possible reasons which induced irregularity when all parent nodes work regularly
A1 (fuel system)	Wrong fuel added/mixed
B5 (misalignment)	Not precisely assembled in the assembly phase

In the condition of all parents working regularly, the irregular probability for this type is 1% by expert judgement.

- Type 2- Material flaw

The irregular states of these nodes, given that all parents are regular, are usually damaged by objects, such as a foreign objects and material degradation.

Table 4-14. Type 2 nodes for human perception analysis

Type 2 nodes	Possible reasons that induce irregularity when all parent nodes work regularly
A3 (hydraulic control system)	False information by DCS
A5 (secondary air-cooling system)	Blocking of cooling holes, operation in the wrong environment
B4 (TBC spallation)	Damage by foreign objects
B10M (mechanical vibration)	Degradation of blading material
C2 (combustor)	Degradation effect, flashback due to poor gas quality
D3 (combustion chamber)	Hot gas path degradation effect
D4 (turbine)	Hot gas path degradation effect

In the condition that all parents work regularly, the irregular probability for this type is 0.1% according to expert judgement.

- Type 3- Other conditions

The chance of these components or functions failing is rare if all parents work regularly. The failure probabilities are tiny and are for some unexpected reasons. For example, the UPS might fail after thousands of times of operation.

- A4 (digital control system)
- A6 (UPS)
- B1 (overspeed)
- B2 (sealing rupture)
- B3 (blading rupture)

- B6T (thermal overheating)
- B6M (mechanical overheating)
- B10T (thermos-acoustic induced vibration)
- C1 (compressor blading)
- C3 (turbine blading)
- C4 (bearing)
- C5 (AC pump)
- C6 (DC pump)
- D1 (rotor)
- D2 (compressor)

In the condition that all parents work regularly, the irregular probability for this type of node was given 0.1% by expert judgement.

4.3.2. The Relation between Human Perception and Output

A correlation coefficient is required to explore the relationship between human perception and model output. First, eight different probabilities were assigned, representing eight different values of human perception. Then, eight different probabilities of Group D nodes were calculated based on the inference analysis, representing the probability distribution of the system outcome state. After these, the correlation coefficient can be calculated using the Karl-Pearson correlation coefficient formula (see Equation 3-2).

➢ Type 1- Operation error

To demonstrate the influence of human perception in the Type 1 nodes on the model, only human perception in the Type 1 nodes was changed, while the values of the Type 2 and Type 3 nodes were both fixed at 0.1%. The irregular probabilities of Group D were then calculated and shown in Table 4-15.

Table 4-15. Irregular probabilities of Group D given different human perception in Type 1 nodes

Human perception in Type 1 nodes		0	0.10%	0.50%	1.00%	2.00%	3.00%	5.00%	10.00%
Irregular probability of Group D	D1=I	3.01%	3.40%	4.94%	6.83%	10.44%	13.86%	20.16%	33.28%
	D2=I	1.43%	1.61%	2.29%	3.13%	4.78%	6.37%	9.41%	16.25%
	D3=I	1.56%	1.75%	2.52%	3.47%	5.33%	7.13%	10.59%	18.46%
	D4=I	3.98%	4.50%	6.55%	9.03%	13.77%	18.22%	26.35%	42.88%

Based on Table 4-15, the correlation coefficients between perception and the output of group D were calculated, which were 0.9969, 0.9990, 0.9992, and 0.9961, respectively. These results indicated significant correlations between human perception in Type 1 nodes and the irregular probabilities of Group D. As shown in Figure 4-4, these correlations were positive.

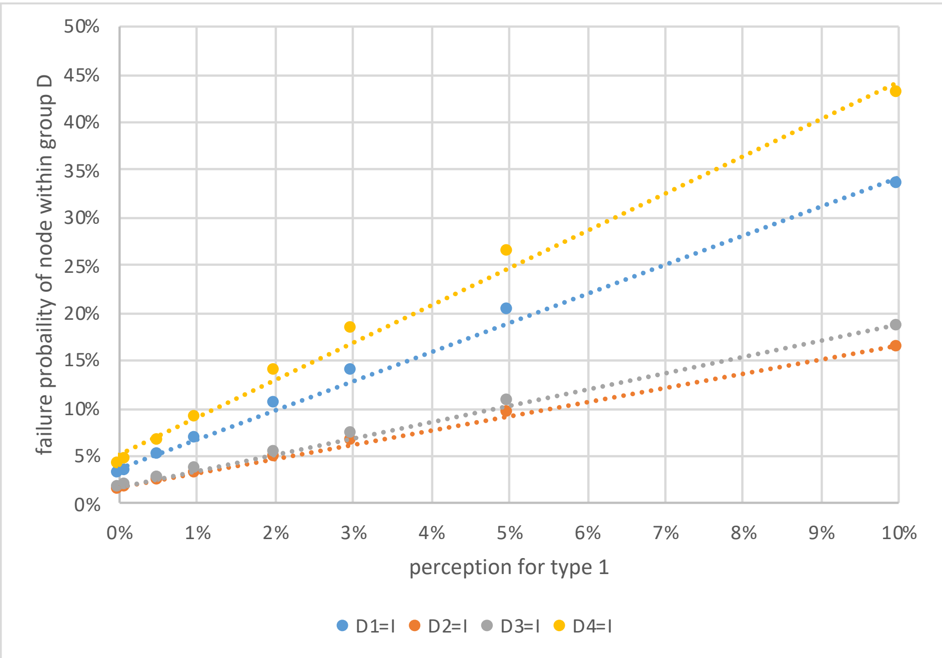


Figure 4-4. Irregular probabilities of Group D given different human perceptions in Type 1 nodes

➢ Type 2- Material flaw

To demonstrate the influence of human perception in Type 2 nodes on the model, only the human perception of Type 2 was changed, the values of Type 1 and Type 3 were fixed at 1% and 0.1% respectively. The results of group D were calculated and shown in Table 4-16.

Table 4-16. Irregular probability of group D given different perceptions for type 2

Human perception of Type 2 nodes		0	0.01%	0.05%	0.10%	0.20%	0.30%	0.50%	1.00%
Irregular probability of Group D	D1=I	6.16%	6.23%	6.49%	6.83%	7.48%	8.14%	9.42%	12.53%
	D2=I	2.90%	2.92%	3.02%	3.13%	3.37%	3.60%	4.60%	5.20%
	D3=I	2.97%	3.02%	3.22%	3.47%	3.97%	4.47%	5.46%	7.88%
	D4=I	7.96%	8.07%	8.50%	9.03%	10.08%	11.12%	13.15%	18.02%

Based on Table 4-16, the correlation coefficients between perceptions and the output of each node within Group D were 0.9999, 0.9761, 0.9999, and 0.9998, respectively, indicating significant correlations between human perception in Type 2 nodes and the output of Group D. Furthermore, Figure 4-5 showed that these correlations were positive.

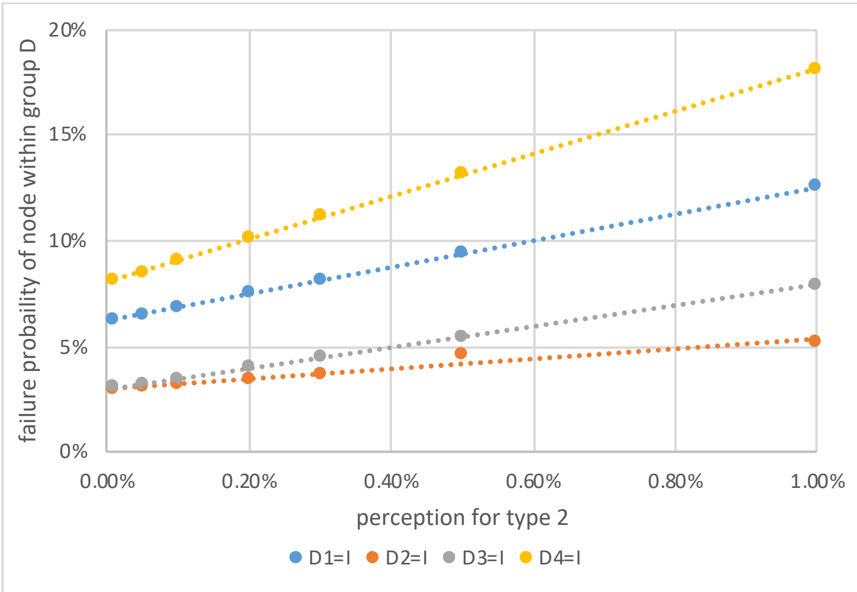


Figure 4-5. Irregular probabilities of Group D given different human perceptions in Type 2 nodes

➢ Type 3- Other conditions

To show the influence of human perception in Type 3 nodes, only human perception was changed in Type 3 nodes, while the values of Type 1 and Type 2 were fixed at 1% and 0.1% respectively. The results of Group D were calculated and shown in Table 4-17.

Table 4-17. Irregular probabilities of group D given different perceptions for Type 3 nodes

Perception for type3		0.00%	0.01%	0.05%	0.10%	0.20%	0.30%	0.50%	1.00%
Irregular probability of group D	D1=I	4.68%	4.90%	5.76%	6.83%	8.91%	10.93%	14.81%	23.58%
	D2=I	1.98%	2.10%	2.56%	3.13%	4.26%	5.37%	7.55%	12.70%
	D3=I	2.48%	2.58%	2.98%	3.47%	4.45%	5.41%	7.30%	11.77%
	D4=I	6.41%	6.67%	7.73%	9.03%	11.57%	14.03%	18.72%	29.52%

The correlation coefficients between perception in Type 3 nodes and outputs of each node within Group D were 0.9991, 0.9997, 0.9998, and 0.9992, respectively, indicating significant correlations between human perception in Type 3 nodes and the output of Group D. Figure 4-6 showed these correlations are positive.

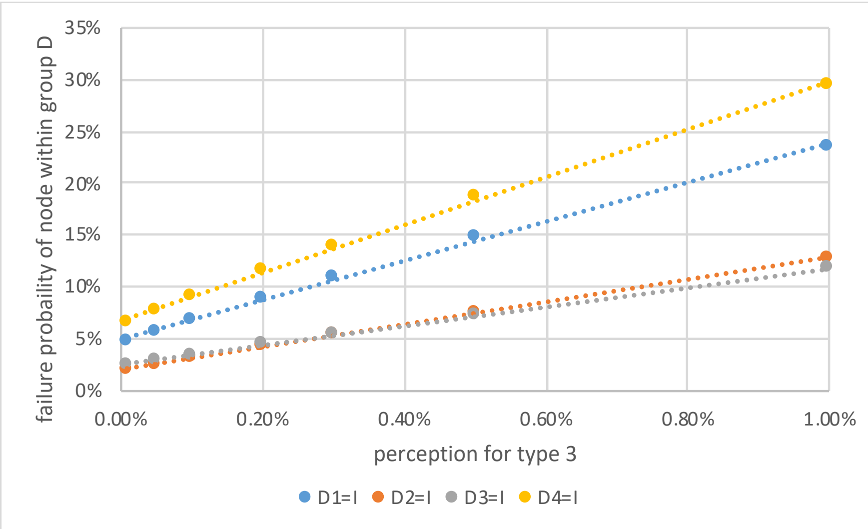


Figure 4-6. Irregular probabilities of Group D given different perceptions for Type 3 nodes

Therefore, probabilities based on human perception in all three types of nodes were positively correlated with the output Group D.

4.3.3. The Sensitivity Coefficient of Human Perception

The sensitivity analysis of human perception, introduced in Section 3.2.2, was conducted. The sensitivity coefficient can be calculated following Equation 3-3. Initially, values based on human perception were 1%, 0.1%, and 0.1% for Type 1, Type 2, and Type 3, respectively. These values were used as baseline values for human perception.

For example, the sensitivity coefficient of D1 was calculated with respect to various values of human at Type 1 nodes based on Table 4-15. When the value of human perception in Type 1 changed from 1% to 0, the sensitivity coefficient was:

$$Sensitivity\ Coefficient = \frac{\Delta output/output\ baseline}{\Delta perception/perception\ baseline} = \frac{(3.01\%-6.83\%)/6.83\%}{(0-1\%)/1\%} = 0.5593 \qquad \textit{Equation 4-4}$$

The sensitivity coefficients of Group D for various values of human perception in Type 1 nodes were calculated based on Equation 4-1 and shown in Table 4-18. The sensitivity coefficient varied from 0.43 to 0.56 in Table 4-18, suggesting that the degree of change in the output would be around half of the degree of change in the value of human perception in Type 1 nodes.

Table 4-18. Sensitivity coefficient of Group D for various values of human perception in Type 1 nodes

Perception for type1		0	0.10%	0.50%	1.00%	2.00%	3.00%	5.00%	10.00%
Sensitivity coefficient of group D	D1=I	0.5593	0.5580	0.5534		0.5286	0.5146	0.4879	0.4303
	D2=I	0.5431	0.5396	0.5367		0.5272	0.5176	0.5016	0.4657
	D3=I	0.5504	0.5508	0.5476		0.5360	0.5274	0.5130	0.4800
	D4=I	0.5592	0.5574	0.5493		0.5249	0.5089	0.4795	0.4165

Table 4-19. Sensitivity coefficient of Group D regarding various values of human perception in Type 2 nodes

Perception for type2 nodes		0.00%	0.01%	0.05%	0.10%	0.20%	0.30%	0.50%	1.00%
Sensitivity coefficient of Group D	D1=I	0.0981	0.0976	0.0996		0.0952	0.0959	0.0948	0.0927
	D2=I	0.0735	0.0745	0.0703		0.0767	0.0751	0.1174	0.0735
	D3=I	0.1441	0.1441	0.1441		0.1441	0.1441	0.1434	0.1412
	D4=I	0.1185	0.1181	0.1174		0.1163	0.1157	0.1141	0.1106

Similarly, the sensitivity coefficients of Group D with respect to human perception in Type 2 nodes are shown in Table 4-19, and the range was 0.07 to 0.145.

As for Type 3, the range of sensitive coefficient was from 0.25 to 0.37 (see Table 4-20).

Table 4-20. Sensitivity coefficient of Group D concerning various values of human perception in Type 3 nodes

Human perception in Type3 nodes		0.00%	0.01%	0.05%	0.10%	0.20%	0.30%	0.50%	1.00%
Sensitivity coefficient of Group D	D1=I	0.3148	0.3140	0.3133		0.3045	0.3001	0.2921	0.2725
	D2=I	0.3674	0.3656	0.3642		0.3610	0.3578	0.3530	0.3397
	D3=I	0.2853	0.2850	0.2824		0.2824	0.2795	0.2759	0.2658
	D4=I	0.2901	0.2904	0.2879		0.2813	0.2769	0.2683	0.2521

Furthermore, the ranges of numbers in the three tables of sensitivity coefficients indicated that the output of the model is more sensitive to perception in Type 1 than the other two types.

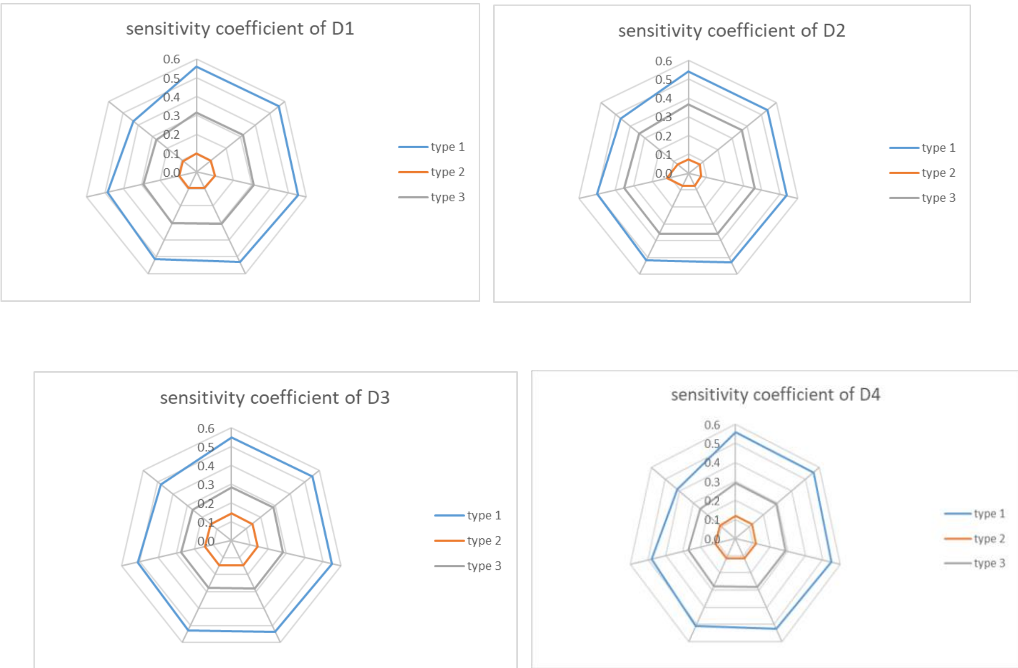
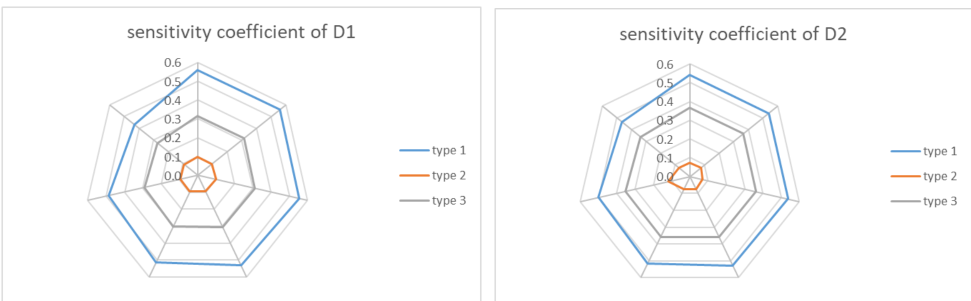
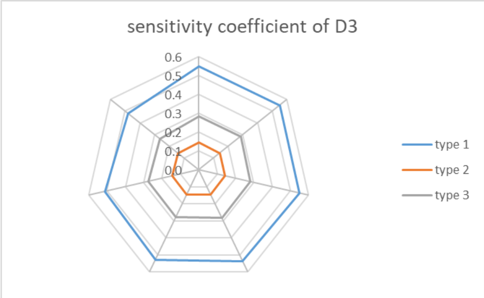


Figure 4-7 shows values with Type 1 nodes were the highest, while those of Type 2 nodes were the lowest. Thus, human perception in Type 1 nodes, which stands for operation error, is the most sensitive parameter in this model.





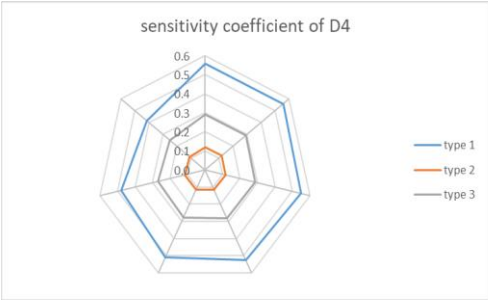


Figure 4-7. Sensitivity coefficient of Group D nodes regarding the difference in human perception for each type nodes

However, one should be aware that the perception baseline for Type 1 nodes was 1%, while the others were 0.1%. If we use 0.1% as the baseline for the Type 1 nodes to calculate the sensitivity coefficient of D1, which means that the 'output baseline' and the 'perception baseline' were fixed at 3.40% and 0.1% individually, according to Table 4-15, then the results were calculated:

$$Sensitivity\ Coefficient = \frac{\Delta output/output\ baseline}{\Delta perception/perception\ baseline} = \frac{(3.01\%-3.40\%)/3.40\%}{(0-0.1\%)/0.1\%} = 0.1147 \qquad \text{Equation 4-5}$$

The value was much smaller than the one based on 1% human perception (see the result of Equation 4-4). Therefore, the most sensitive human perception is related to operation error, because experts believe that operation error is more frequent than other causes.

4.3.4. Conclusion of Human Perception Analysis

The sensitivity analysis showed a significant positive correlation between human perception and model output. Furthermore, the most sensitive parameter was the one that had the highest human perception value at baseline.

Chapter 5. Modelling for Human Performance Included System and Human Error Analysis

Compared to the Human Performance Separated System (HPSS), the Human Performance Included System (HPIS) is an integrated system with complex variables, including the human, the organization, and the environment, in addition to hardware. In such a system, human performance is usually involved. This chapter introduces how the Bayesian Network (BN) modelling can be used as an assessment model for an HPIS failure in the industry. Two methods have been applied for human error analysis. These two methods approach the modelling process from different perspectives. One method focuses on human errors and aims to figure out what causes human errors from a cognitive perspective. The other method treats human errors as an essential part of an HPIS and seeks to determine the role of human errors in such a system. These two methods show differences in taxonomy (a predefined classification scheme) and model structure. Such a methodology is a combination of causation modelling and human reliability analysis (HRA). It considers the human factor as a part of the industry system. Two different methods for human error analysis show that this modelling can examine human errors from different perspectives and can be applied to various HPIS systems.

5.1. Taxonomy for an HPIS Model

5.1.1. Taxonomy of Human Errors in HPIS based on a Cognitive View

Cognition is related to how we understand the world. The taxonomy in this section aims to classify the causation of human errors by viewing human errors as part of the cognitive process. Due to its robustness and efficiency, this taxonomy is expected to provide a clear structure and specific information about the role of human cognitive functions in HPIS. As the focus is on the human cognitive process, other parts of the system are thus treated as potential triggers for human errors. That is, other parts within HPIS are not supposed to influence how the human brain works, but to provide information to human. Meanwhile, the flow of the cognitive process, including retrieving information, thinking, and evaluating, is not supposed to differ significantly in the industrial sectors. Therefore, it is plausible to create a universal taxonomy for human cognitive processes.

Table 5-1. Taxonomy of CREAM

<table>
<tr><th>Category</th><th>Group</th><th>Sub-group</th><th>Contributor details</th></tr>
<tr><td rowspan="7">Human</td><td colspan="2">Wrong action</td><td>Wrong time, wrong type, wrong object, and wrong place</td></tr>
<tr><td rowspan="3">Specific cognitive function</td><td>Observation failure</td><td>missed observation, false observation, and wrong identification</td></tr>
<tr><td>Interpretation failure</td><td>Faulty diagnosis, wrong reasoning, decision error, delayed interpretation, and incorrect prediction</td></tr>
<tr><td>Planning failure</td><td>Inadequate plan and priority error</td></tr>
<tr><td rowspan="2">Person-related function</td><td>Temporary person-related functions error</td><td>Memory failure, fear, distraction, fatigue, performance variability, inattention, physiological stress, and psychological stress</td></tr>
<tr><td>Permanent person-related functions error</td><td>Functional impairment, cognitive style, and cognitive bias</td></tr>
<tr style="display:none"></tr>
<tr><td rowspan="4">Technology</td><td colspan="2">Equipment failure</td><td>Equipment failure and software failure</td></tr>
<tr><td colspan="2">Procedure error</td><td>Inadequate procedure</td></tr>
<tr><td rowspan="2">Man-machine interface problem</td><td>Temporary interface problem</td><td>Access limitations, ambiguous information, and incomplete information</td></tr>
<tr><td>Permanent interface problem</td><td>Access problems and mislabelling</td></tr>
<tr><td rowspan="5">Environment</td><td colspan="2">Communication failure</td><td>Communication failure, missing information</td></tr>
<tr><td colspan="2">Organization problem</td><td>Maintenance failure, inadequate quality control, management problem, design failure, inadequate task allocation, and social pressure</td></tr>
<tr><td colspan="2">Training problem</td><td>Insufficient skill and insufficient knowledge</td></tr>
<tr><td colspan="2">Ambient condition problem</td><td>Sound, humidity, adverse ambient conditions, illumination, and temperature</td></tr>
<tr><td colspan="2">Working condition problem</td><td>Excessive demand, inadequate workplace layout, inadequate team support, and irregular working hours</td></tr>
</table>

As the human brain is rather complex, there is no perfect method to create a taxonomy that includes all human factors. In this dissertation, we develop a new scheme based on a previous taxonomy, known as the Cognitive Reliability and Error Analysis Method (CREAM) with some modifications. The CREAM was proposed by Hollnagel (1998). As a popular method for human reliability analysis (HRA), CREAM offers a clear and practical division of human, technological, and organizational factors in human errors (see Table 5-1).

As mentioned in Chapter 2, more data are required for more nodes. An enormous dataset would be required if all nodes of contributors are included in the model. Therefore, this taxonomy has been simplified by reducing the number of nodes.

To achieve this, the nodes for the HPIS model were adapted only from the group / subgroup columns of Table 5-1. Another reason to give up the last column ('contributor details') as the nodes in Table 5-1 is that the details of some contributors are similar and are not easily distinguished from each other in the industry. As for the human category, subgroups (e.g., wrong action, observation failure) have been chosen as nodes in the model, which are more specific than the group column. Regarding the technological and environment categories, the group column (e.g., equipment failure) was used as nodes for the same reason.

Table 5-2. A simplified taxonomy adapted from CREAM

Category	Nodes used for the HPIS model
Human	Wrong action, observation failure, interpretation failure, planning failure, temporary person-related function error, and permanent person-related function error
Technology	Equipment failure, procedure error, and man-machine interface problem
Environment	Communication failure, organization failure, training problem, ambient condition problem, and working conditions problem

Table 5-2 shows the simplified taxonomy for identifying human, technological, and environment factors that trigger human errors.

5.1.2. Taxonomy of HPIS Failure in a Specific Industry Sector Concerning Human Errors

Human factor is an essential component of many industries. Cognition is only part of the function of the human brain. When human errors in a specific industry sector are examined, one must consider the broad background of the industry. For example, one or more streamlines are involved in the industry that consists of the production of goods. During production, one or several organizations must join relevant activities with appropriate methods and equipment in designated spaces while investing money and time. There are common features related to human errors in the HPIS. However, industry sectors vary in degree of mechanization, frequency, and accuracy of operation demand and require different financial schemes and environments. This diversity may change the role of the human factor from sector to sector. Therefore, to deal with the influence of human errors on HPIS, developing a specific model for a particular industry sector is more reliable than a universal one.

Thus, to develop a taxonomy for the HPIS system, we must create a framework with basic categories. Since there is no standard way to do this, a new method has been proposed (see Table 5-3).

Table 5-3. A taxonomy framework to build the HPIS model

Category	Explanation
Human	Human factors, such as action, physical/psychological condition, cognition, knowledge, and skill
Resource	Physical things used during production, such as raw material, energy power, mechanical control system (including software), equipment and tools
Workplace	Scenes where the production takes place, such as site layout and site environment

Process	Immaterial things required during the production, such as design, method statement, inspection, daily working shift (including overtime), housekeeping
Organization	Intangible things within groups/organizations who are involved in the production, referring to company culture, rules, management structure, financial situation, timetable limit

Based on this framework, we may elaborate and cross-check all contributors with expert knowledge (including relative research work) and then decide whether to keep, ignore, or combine them.

5.2. A Hybrid Method to Ascertain Dependency Links

Traditional methods to develop dependency links, known as expert judgement and mathematical analysis, have some limitations. Expert judgements may vary and can be arbitrary. Mathematical analysis requires sufficient data, which may not be available in many situations. A hybrid method that combines expert judgement with mathematical analysis could be a potential solution. The dependency links could be identified using mathematical analysis first, then modified by expert judgement, and vice versa.

5.2.1. Expert Judgement on Dependency Links

The expert evaluation questionnaire is used to gather the expert judgement. Table 5-4 shows an example of such a questionnaire.

Table 5-4. Questionnaire of dependency links

Contributor \ Consequence	I	II	III	IV	V
I					
II					
III					
IV					
V					

The expert is asked to cross-check each pair and put the weight to stand for the dependence links.

- A score of 3 indicates a strong dependence (there is a dependency link).
- A score of 1 indicates a weak dependence (there may or may not be a dependency link).
- A score of 0 indicates no dependence at all (there is no dependency link).

To fill in the table, experts are suggested to follow some principles and guidelines, which are the same as the Procedure for Building Dependency Arrows for HPSS (see Section 3.1). For example, cyclic links should be avoided because the BN model is an acyclic graph. That is why the hierarchy rule is usually recommended, for example, I → II / III → IV / V.

As the judgement of one expert can be biased, judgements from multiple experts are required. In this case, an average score of expert judgement should be calculated and compared with a threshold. For example, when the average score is higher than 2/3, it indicates a strong dependency link. When the average score is below 1/3, it indicates a weak or even no dependency link. When the average score is between 1/3 and 2/3, it indicates a vague dependency link, which requires further examination using mathematical independence analysis. In particular, mutual links are not excluded in the questionnaire because experts may have opposite judgements. The one with a higher total score should be kept. However, it is still possible that two identical scores appeared for both directions of the mutual link. Section 3.1.3 recommends some solutions for this rare situation and for cyclical relations. We report an example in Section 7.3.

5.2.2. Mathematical Independence Analysis

As mentioned in Section 2.3.2, the independence test focuses on pairs of variables, as indicated in Table 5-4. Table 5-5 shows an example of the results of the independence test.

Table 5-5. Example of independence test results

	I	II	III	IV	V
I					
II	Independent				
III	Independent	Independent			
IV	Independent	Dependent	Dependent		
V	Dependent	Independent	Dependent	Independent	

The results of the independence test are probabilities of dependency instead of binary judgements, as indicated by yes/no answers. To define a dependency link, the value must be greater than 99% or even be 99.9%. Then, expert judgement is introduced to complement the mathematical analysis. In other words, we keep dependency links with high probabilities and let experts define the rest using their judgement. See Section 2.3.2 for more discussion.

However, the independence test only shows if the two variables are dependent but cannot tell the casual relations, which can be determined by expert judgement before or after the mathematical analysis.

5.2.3. Sequence of Dependency Analysis

The sequence of performing the dependency analysis, with either a mathematical analysis first or an expert judgement first, should be determined by the data quality and expertise of the experts. Usually, a more reliable analysis should be performed first.

Usually, it is difficult to identify the cause of human errors from a cognitive perspective in the industry because cognition is rather complex, and experts with different expertise may diverge in their opinions. Thus, mathematical analysis may be a better choice when expert judgement is unreliable. In contrast, in a particular industry sector, experts may have more consensus than divergence. Thus, expert judgement can be conducted before using the mathematical method for dependency analysis.

5.3. Parameter Learning

Expert judgement is not reliable for defining parameters for the HPIS model, because it is difficult to estimate the dependency strength between human and organization in the HPIS. Mathematical analysis, known as parameter learning in BN, is often used to calculate the dependency links between human and organization in the HPIS instead. This method calculates the frequency that populates each value within the CPT under the combination of states of parents. The frequency is used to decide the probability of the root node (see Section 2.2.2).

5.4. Human Error Analysis in HPIS Failure

Human error analysis over a complex system aims to explore the role of human errors as causes or consequences. When human errors are defined as causes, this analysis focuses on comparing the influence of human errors and other factors on HPIS failure. When human errors are defined as consequences, the analysis aims to explore the causes behind these errors. A typical analysis method is the BN inferencing method for diagnosis and prediction. Generally speaking, a what-if analysis can be used to infer the influence of contributors.

5.4.1. What-if Diagnosis

What-if diagnosis is used to build a hypothetical undesirable consequence and diagnose the probability distribution of contributors. The probability value indicates the probability of each contributor. The most probable contributor is exposed with the highest value with an irregular state. Furthermore, the influence paths can be compared, and the most critical path can be located. The idea is to assume an irregular consequence, calculate the irregular probability of all contributors and then find the path composed of contributors with higher values.

Figure 5-1 shows a diagnosis with an example of a what-if model. In this model, the outcome of the system is assumed to be irregular. The values beside each node are the probability of it being irregular and regular, respectively.

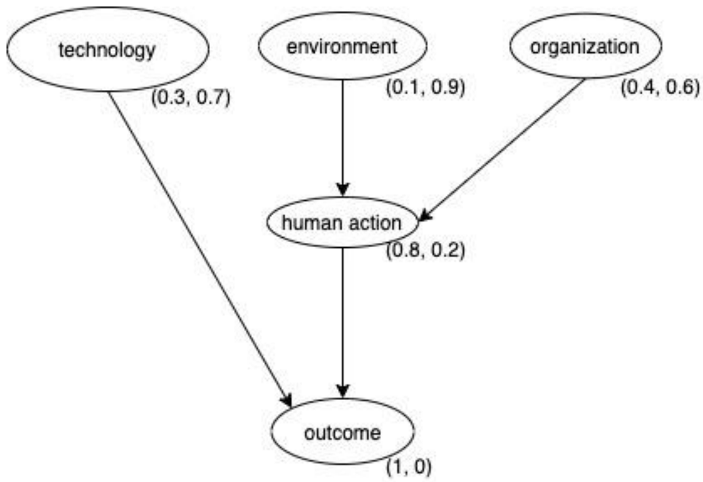


Figure 5-1. An example of what-if diagnosis analysis

Figure 5-1 shows that the probability of human action is much higher than that of other contributors to the irregularity of the system. To locate the path, the parents of the human factors are then compared with each other. Since the irregular probability of the organization is higher than the environment, the path 'organization → human action → outcome' is more likely to contribute to the irregularity of the system than other paths. In this example, the outcome of the system is treated as the consequence node, while human action (a type of human error) as the cause. Similarly, human action can be treated as the consequence node with an undesirable state. Then, through the diagnosis process, we can explore the probabilities of contributors. The diagnosis results are supposed to facilitate the identification of trigger(s) more efficiently.

5.4.2. What-If Prediction

Apart from locating the trigger by what-if diagnosis, we shall discuss how vital the trigger is and what the benefit is when the trigger is removed or mitigated. For this purpose, a what-if prediction can be used to see what would happen to the consequent node given a specific state of the contributor node. The idea of a what-if prediction is to assume a particular state of the contributor node and calculate the probability of the consequence node. Two different (usually opposite) assumptions are given to the same contributor node, and two separate consequence probability distributions are calculated and compared to obtain the weight indicating the importance of the contributor node. See Equation 5-1 for the definition of the weight that is used to quantify the significance of the contributor node:

$$Weight\ (\text{contributor} \rightarrow consequence) = \frac{consequence\ difference}{consequence\ baseline} \qquad \textit{Equation 5-1}$$

where:

weight is the critical quantity of contributor node to consequence node.

The consequence baseline is the probability of consequence given the first assumption for the contributor state.

The consequence difference is the difference between the consequences given another assumption for the contributor state and the consequence baseline.

The weight value should be ranged from [-1,1]. A higher absolute value indicates a more significant influence of the contributor. A positive value indicates that the contributor impact consequence positively, whereas a negative value indicates a negative influence.

Chapter 6. Assessment Model for Human Error in Human Performance Included System from Cognitive View

This chapter builds a Bayesian Network (BN) model based on a taxonomy, known as the Cognitive Reliability and Error Analysis Method (CREAM), for the Human Performance Included System (HPIS). Compared to previous studies and the next chapter, in this chapter, human factors, specifically the wrong action of workers, were treated as consequences of the HPIS. First, it reports the modelling process, including the taxonomy of nodes, dataset, and identification of the network structure and parameters. Then, the contributors to human errors were weighted and compared. Using an existing dataset, this BN model is used as an example to demonstrate how BN modelling can be used to improve traditional human reliability analysis (HRA). Our model has a clear structure and provides numerical weight to contributors. This information is important for making decisions that can facilitate the control of risk factors. In addition, this BN model can be used as an example of its application in various industrial sectors.

6.1. Modelling Process

6.1.1. Taxonomy of Nodes

The taxonomy of nodes used in this chapter was adapted from

Table 5-2.

6.1.2. Dataset Converted from Multi-Attribute Technological Accidents Dataset (MATA-D)

MATA-D was developed by Raphael Moura (Moura et al., 2014). It contains 238 major accidents in different industries. The dataset was originally designed to fit the taxonomy of contributors in Table 5-1 but was converted to fit the taxonomy in Table 5-2. All contributors were kept as binary variables. The state of nodes (second column in Table 6-1) was coded as irregular when a problem was identified in the accident reports. Nodes were registered as regular only when no problem was identified in accident reports. The complete converted MATA-D dataset can be found in Appendix B. Table 6-1 shows the statistical results of the converted MATA-D.

Table 6-1. Data classification results

Category	Contributor node	Frequency*	
		#	%
Human	Wrong action	125	52.52%
	Observation failure	47	19.75%
	Interpretation failure	79	33.19%
	Planning failure	38	16.97%
	Temporary person-related function error	31	13.03%
	Permanent person-related function error	18	7.56%
Technology	Equipment failure	134	56.30%
	Procedure error	105	44.12%
	Man-machine interface problem	51	21.43%
Environment	Communication failure	69	28.99%
	Organization failure	224	94.12%
	Training problem	129	54.20%
	Ambient condition problem	21	8.82%
	Working conditions problem	27	11.34%

* *Number of events in which contributors appeared*

6.1.3. Dependency Links

We first developed an assessment model that explored the cause of human errors from a cognition point of view. To simplify the model, we focus on links that refer to cognitive functions and wrong actions while ignoring other links. To find dependency links, independence tests, known as the Chi-square test (see Section 2.3.2), were conducted. Table 6-2 shows the results of the $\chi 2$ test.

Table 6-2. Results of the χ2 test

Contributor	Wrong action	Planning error	Interpretation error	Observation error
Planning failure	*70.6177*			
Interpretation failure	*18.152*	*19.05*		
Observation failure	*55.3853*	1.1601	*11.0527*	
Communication failure	*27.2855*	*11.5856*	0.9806	5.5169
Person-related Temporary function error	*84.2535*	0.8305	*27.2405*	3.9253
Person-related permanent function error	*114.4443*	8.0952	*48.1788*	*14.9847*
Man-machine interface problem	*49.367*	2.3356	8.2967	0.2056
Equipment failure	0.686	*83.8972*	*25.7038*	*67.4753*
Ambient condition problem	*106.8579*	5.5914	*42.5868*	*11.598*
Procedure error	3.3651	*44.8721*	5.989	*32.5143*
Training problem	0.1351	*76.3862*	*21.3476*	*60.6179*
Working condition problem	*92.8262*	2.1559	*32.8175*	6.4004
Organization problem	*110.6707*	*300.5958*	*197.2176*	*275.2037*

Only pairs with $\chi^2 \geq 10.828$ indicated more than 99.9% probability of a dependency relationship, and thus were regarded as holding a dependent link. This is not a strict threshold but may vary in studies. To determine the direction of the links, expert judgement must be used. Additionally, arrowheads must be added to the links. Although the CREAM describes potential contributors of each factor used in the links, the logical decision was used to find contributors that were not otherwise identified. Table 6-3 shows all dependencies.

Table 6-3.Dependencies table for the human error analysis model

Consequence	Contributor
Wrong action	Observation failure, interpretation failure, planning failure, communication failure, temporary person-related function error, permanent person-related function error, interface problem, ambient condition problem, working condition problem, organization problem
Planning failure	Interpretation failure, communication failure, equipment failure, procedure problem, training problem, organization problem
Interpretation failure	Observation, temporary person-related function error, permanent person-related function error, equipment failure, ambient condition error, training problem, working condition problem, organization problem
Observation failure	Permanent person-related function error, equipment failure, ambient condition problem, procedure problem, training problem, organization problem

6.1.4. Network Structure

The causal graph, which represents the network structure, was developed to show the model structure (see Figure 6-1).

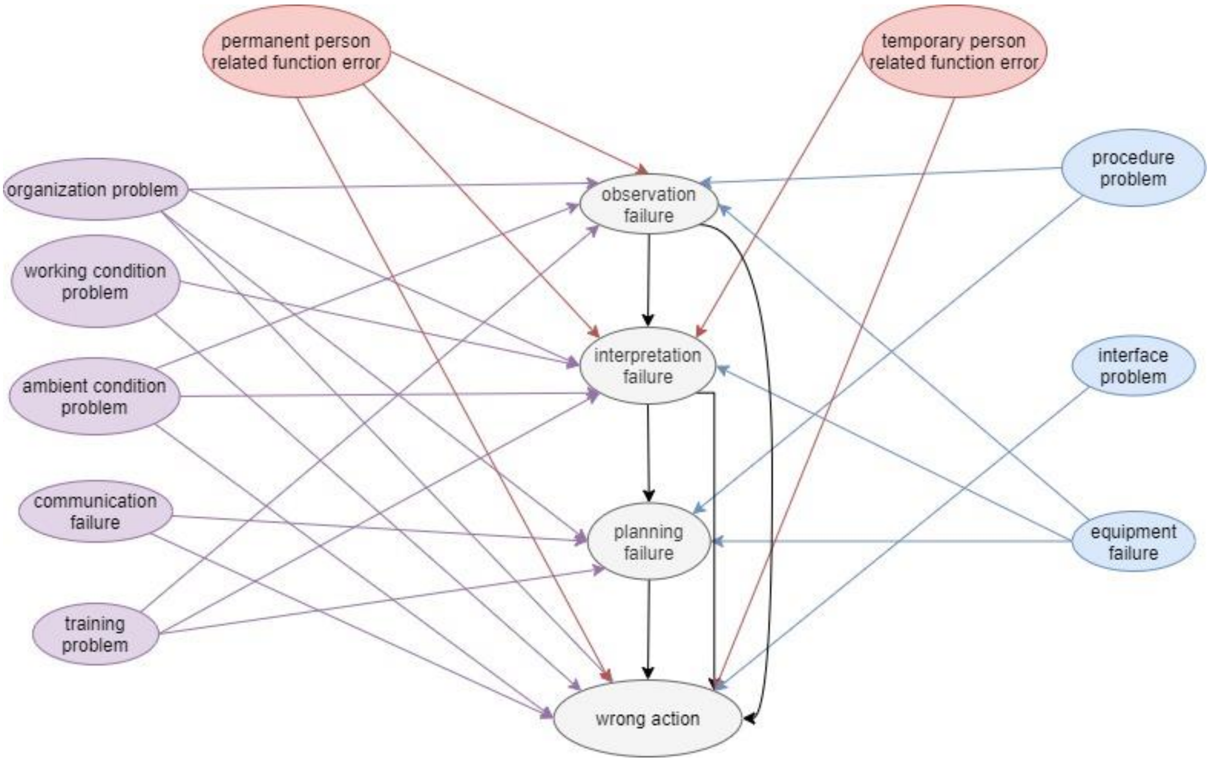


Figure 6-1. Causal graph for human error analysis based on the CREAM

6.1.5. Conditional Probability Table

The parameter learning process was developed with all the data from the converted MATA-D dataset, following Bayesian parameters updating routine provided by the Bayesian Network Toolbox within Matlab. A uniform distribution was given as a prior probability for all nodes to aid in parameter learning.

6.1.6. Model Validity

The model in this chapter was developed using the converted MATA-D dataset, in which the dependency links and probabilities were identified by the BN modelling. The validity of the model was further evaluated on the basis of these links and probabilities. Expert knowledge can be used to check whether the dependency links are reasonable. Erik Hollnagel (1998) presented antecedents of consequences in the CREAM, but they did not specify whether the dependency links were direct or indirect. Table 6-4 shows the difference between the present model and the CREAM

Table 6-4. Differences in dependency link between the present model and the CREAM

Consequence (Child node)	Different parent nodes between the present model and the CREAM	
	Included in our model but not in CREAM	Included in CREAM but not labelled as parent nodes in our model
Wrong action	Permanent person-related function error, ambient condition problem, working condition problem	Procedure failure, equipment failure
Planning failure	Equipment failure, procedure failure, organization failure	Ambient condition problem, working condition problem
Interpretation failure	Ambient condition problem, training problem	Procedure problem
Observation failure	Procedure problem, training problem	Interpretation failure

Although it is unlikely to give an accurate comparison of the dependency links between these two models (say which one is better), we have identified some differences.

First, in the present model, procedure is considered the parent of planning and observation, but not the parent of action and interpretation, as in the CREAM model. The procedure is assumed to indicate how we observe and what we shall do next (planning). In addition, interpretation relies on the human brain, which translates what you see to what you think and requires more skills and knowledge than the procedure. Action refers to motor responses following the cognitive process, but is indirectly influenced by the procedure, just as the equipment.

Second, interpretation and observation are mutually linked in the CREAM model. In the present model, however, observation is treated as a parent of interpretation due to the acyclic principle of the Bayesian Network.

Third, in the present model, wrong actions were associated with problems of ambient conditions and working conditions, but not in the CREAM model. However, the results of the quantity analysis indicate that these links are not strong in the present model (see Figure 6-2).

As the probabilities of nodes are calculated based on the dataset, the quality of the model relies on the quality of the data. Our model demonstrates where the problem may exist, but it only shows the trend but not the accurate probability. Model quality can be examined by using the what-if analysis shown in Section 6.2 (although it is not the initial purpose of writing that section).

In summary, the model in this chapter explores human errors from a cognitive point of view and reveals differences and similarities compared to the CREAM model.

6.2. Weight of Contributors to Human Errors

Figure 6-1 shows the potential causes of human errors. A weighted analysis is used to identify which factor affects the results to a greater extent, according to Section 5.4.2. Each ancestor node was assigned a different state (regular / irregular), while other nodes remained unobserved. The irregular probability of the child node was calculated, as shown in the following function.

$$\text{Weight (contributor} \rightarrow \text{human error)}$$
$$= \frac{[Probability(\text{human error} = \text{I}|\text{contributor} = \text{I}) - Probability(\text{human error} = \text{I}|\text{contributor} = \text{R})]}{Probability(\text{human error} = \text{I}|\text{contributor} = \text{R})}$$

The results were then compared to see which ancestor node(s) significantly influenced the child node. This calculation process was executed with a belief propagation algorithm provided by Bayesian Network Toolbox within Matlab (Murphy, 2003)

6.2.1. Weights of the Contributors to the Wrong Action

Figure 6-2 shows the weights of the contributors to the wrong action. As part of the cognitive process, interpretation has the most significant influence, followed by planning and observation. The other contributors with small absolute values showed little influence on the wrong action.

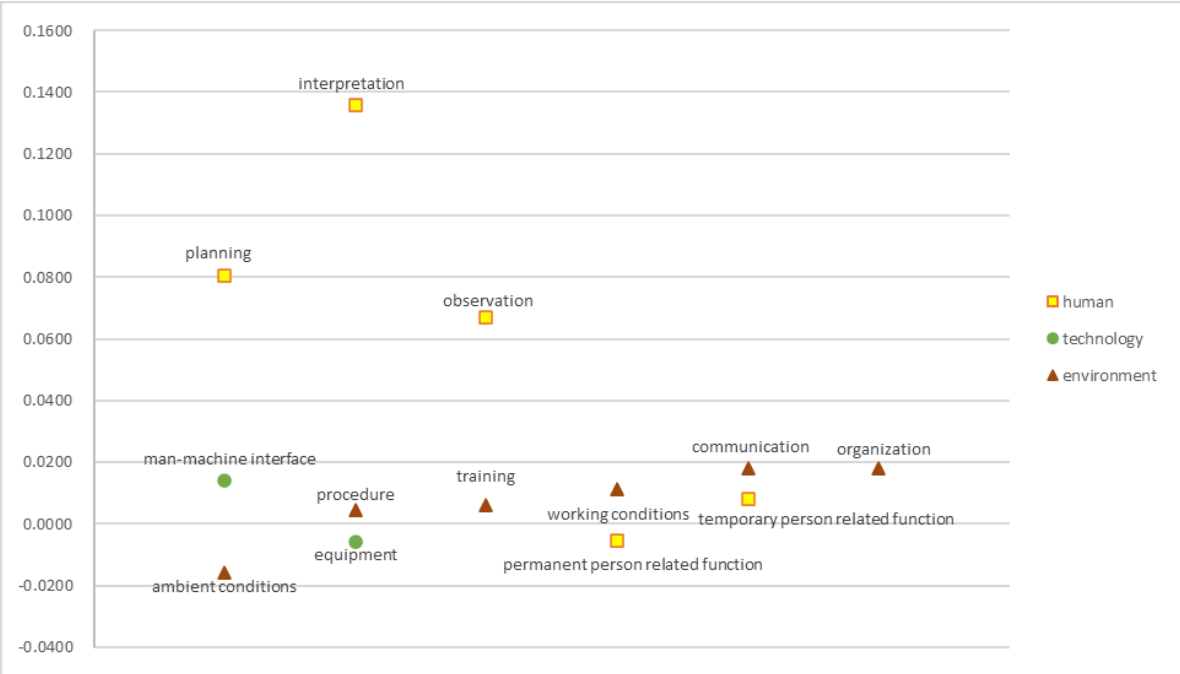


Figure 6-2. Weights of contributors to wrong action

6.2.2. Weights of the Contributors to Planning Failure

Figure 6-3 shows the weights of the contributors to planning failure. Interpretation has the most critical influence on planning failure, indicating its crucial role in the cognitive process. Communication also significantly influences planning due to its role in the planning stage. The weight of training was approximately 5%. This value is not high, but it still indicates the influence of training on planning failure.

When the following contributors were treated as ancestors but not parents, including the ambient conditions, working conditions, observation, and the permanent and temporary functions related to the person, they showed little influence on planning, as indicated by their small absolute weight values. The procedure was treated as a parent node, but its weight was close to zero, suggesting that it had little effect on the planning failure.

As for the equipment node, its weight was negative, suggesting that equipment failure may decrease the probability of planning failure. In some accidents, equipment failure, but not human errors, often causes accidents. The negative influence of organizational problems on planning might be due to improved human performance used to compensate for organizational problems.

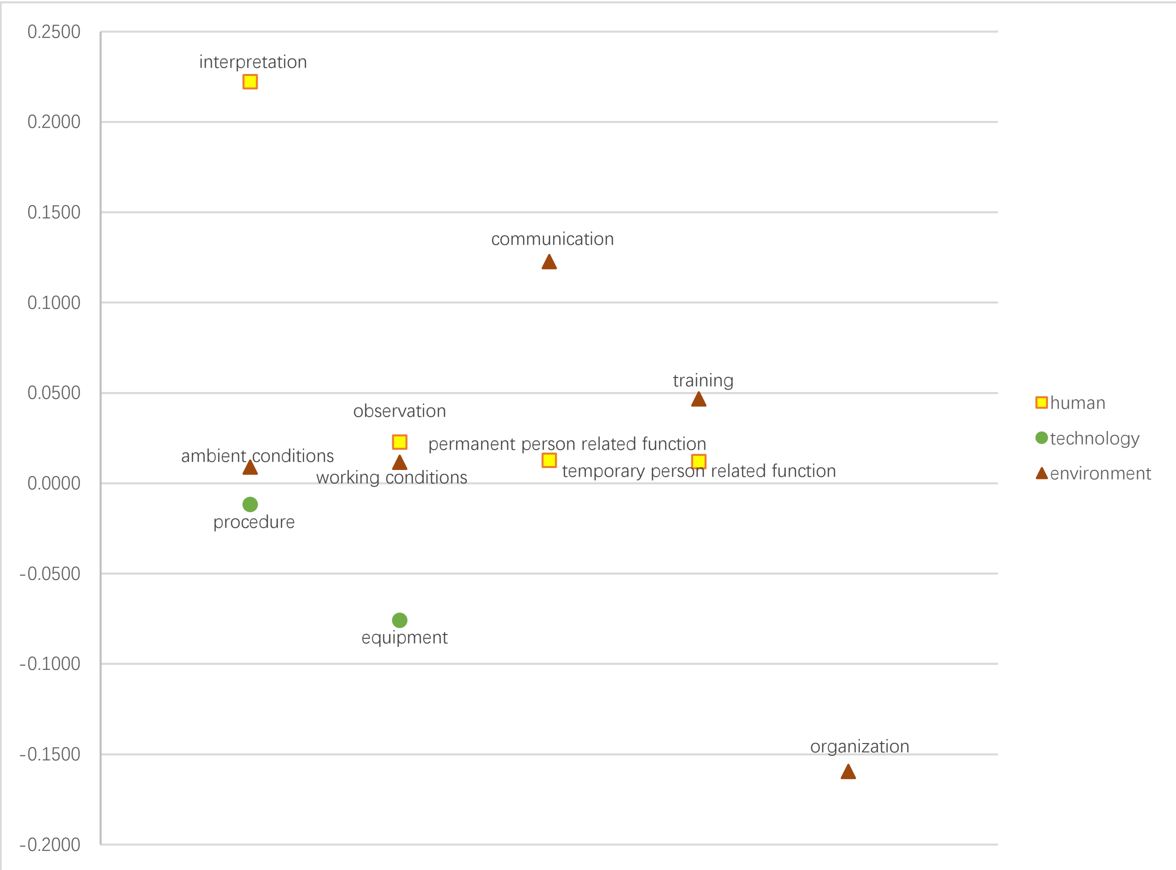


Figure 6-3. Weights of contributors to planning failure

6.2.3. Weights of the Contributors to Interpretation Failure

Figure 6-4 shows the weights of the contributors to interpretation failure. As a crucial part of the cognitive process, interpretation can be affected by six parents in a conspicuous way, including observation, permanent person-related function, temporary person-related function, working conditions, training, and ambient conditions, all of which the weights were above 10%. In terms of equipment and organization, the same issue was found in planning failure.

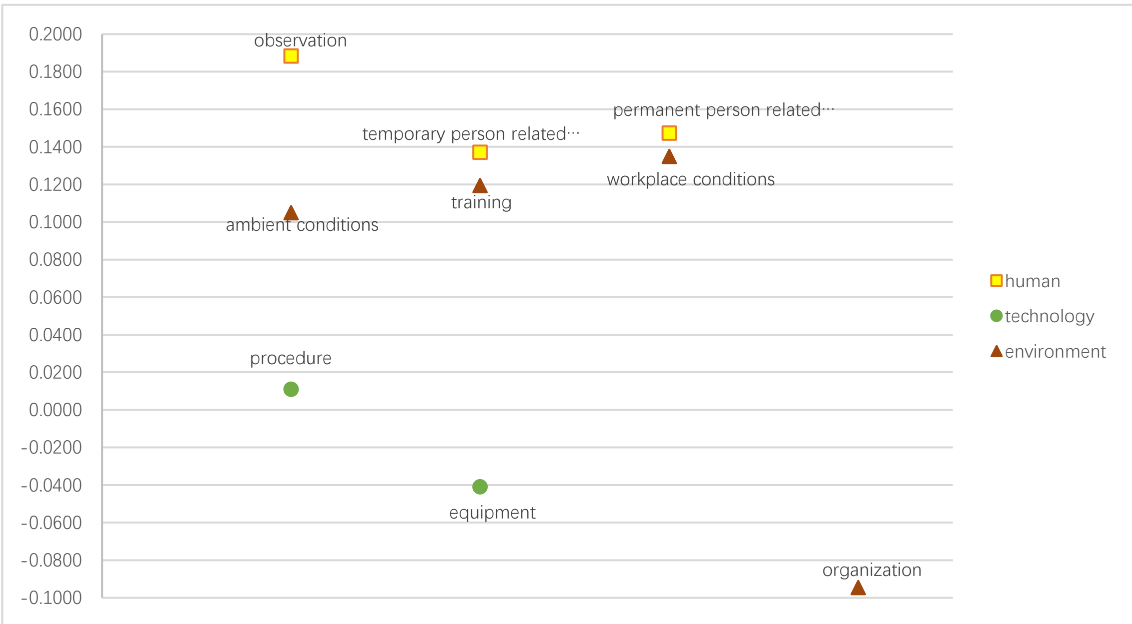


Figure 6-4. Weights of contributors to interpretation failure

6.2.4. Weights of Contributors to Observation Failure

Figure 6-5 shows the weights of all contributors to the observation failure. The problem of permanent person-related function and ambient conditions increased the probability of observation failure by more than 30%, respectively, while procedure problems increased by about 20%. In terms of equipment and organization, the same issue was found in planning failure and interpretation.

As to training problem, the reason for its negative influence on observation, seems to be an illusion by the dataset. Training problem may not induce observation failure. Furthermore, either training problem or observation failure may cause interpretation failure (or wrong action), but they do not occur at same time based on the dataset.

Figure 6-5. Weights of contributors to observation failure

6.3. Conclusion of Human Error Analysis from a Cognitive View

This model shows that interpretation has the most significant influence on wrong action, followed by planning and observation. These variables are closely related to the human cognitive process with several contributors (see Table 6-5). On the contrary, the influence of other contributors was less sensitive to wrong action.

Table 6-5. Significant contributors to the cognitive process

	Contributors with a significant influence on the cognitive process
Planning failure	Interpretation failure, communication failure
Interpretation failure	Observation failure, permanent person-related function error, temporary person-related function error, working conditions problem, training problem, ambient condition problem
Observation failure	Permanent person-related function error, ambient condition problem, procedure failure

According to this model, equipment failure and organization problems are two contributors that have been shown to decrease the probability of human errors in the cognitive process. It is surprising that these two variables improve human cognition in our model. One possibility for these inconsistent results may lie in the accident reports dataset. In some cases, equipment failure has direct consequences, leaving no chance for human errors. Therefore, mathematically, equipment failure may decrease the probability of human errors. As for the organizational problem, there are two possible reasons. On one hand, organizational problems cause wrong action directly, but not harm the cognitive process. On the other hand, if people discover some organization problems, such as maintenance failure, design failure, or inadequate task allocation, they may be more careful during the cognitive process, thus, people compensate for human performance and reduce the probability of cognitive errors.

Chapter 7. Assessment Model for Construction Occupational Accidents and Human Error Analysis

This chapter reports on the building of a BN model for occupational construction accidents in China. It demonstrates how to build a BN model for a Human Performance Included System (HPIS) failure and how to identify the most important contributors and main paths among contributors. Compared with the previous chapter, this chapter focuses not only on human factors but also on other factors that can contribute to the failure of the HPIS. In particular, it reveals how to analyse human errors for construction occupational accidents.

It first introduces a new taxonomy of contributors that was proposed to identify and classify factors related to construction occupational accidents. The proposed taxonomy has been used to guide data collection in this dissertation and can be used in future data collection as well. Then it reports on a Bayesian Network (BN) model that was developed based on 303 occupational accidents collected from the construction industry in China. Finally, it presents the analysis of the impact of contributors especially human errors on accidents.

7.1. Contributors Taxonomy for Construction Occupational Accidents

A new taxonomy was proposed to identify potential contributors to occupational accidents in the construction industry (see Table 7-1).

It should be noted that, besides these contributors, the consequences, namely occupational accident and structure failure, are also nodes of the model. Occupational accident is usually mentioned as a safety accident in construction, while structure failure is always mentioned as a quality accident. Furthermore, structure failure may or may not cause occupational accident.

Table 7-1. Taxonomy of contributors linked with construction occupational accidents

Category	Contributor
Human	Wrong action, physical problem, insufficient skill, poor safety knowledge, communication failure
Resource	Personal Protective Equipment (PPE) failure, machinery problem, material deficiency
Workplace	Site layout problem, site environment problem
Process	Design deficiency, inadequate method statement, insufficient test, irregular working hours, supply/maintenance problem
Organization	Manpower allocation problem, insufficient management system/working rule, insufficient safety training, schedule pressure, economic pressure

7.1.1. Human

The human category, which includes behaviour, physical condition, ability, awareness, and communication of workers, has been consistently associated with construction accidents reported in industry and revealed in previous studies. In our taxonomy, the human category only includes on-site workers, but not people who were involved during design, rulemaking, finance, and schedule planning. Human errors in those stages are complex and should be analysed in separate models.

Table 7-2. Contributors within the human category to occupational accidents in the construction industry

Contributor	Definition/explanation
Wrong action	Wrong action or operation of the worker(s).
Physical problem	Poor work performance due to physical problems, including fatigue, illness, impairment.
Insufficient skill	Lack of skills to complete the work or to use equipment/tools properly, such as welding, measuring, using the crane, etc.
Poor safety knowledge	Lack of safety knowledge/awareness, which is usually described as reckless, careless, or ignorance.
Communication failure	Missing, incorrect, or incomplete information.

7.1.2. Resource

The resource category refers only to physical resources used in the construction industry, such as materials, equipment, and tools. Other resources, such as human resources and technical documents, are not included. Furthermore, according to previous research (Gattuso, 2021; Sehsah et al., 2020), failure of Personal Protective Equipment (PPE) plays a vital role in occupational accidents in the construction industry. Due to the importance of safety performance and the use of personal protection, PPE is considered a separate factor.

Table 7-3. Contributors within the resource category to construction occupational accidents

Contributor	Definition/explanation
PPE failure	Poor condition, usability, or suitability of PPE or lack of PPE
Machinery problem	Poor condition, usability, or suitability of the machine
Material deficiency	Poor condition, usability, or suitability of building material

7.1.3. Workplace

The workplace category refers mainly to the layout and environmental conditions of the construction site.

Table 7-4. Contributors within the workplace category to construction occupational accidents

Contributor	Definition/explanation
Site layout problem	Narrow space, lack of safeguard, improper layout
Site environment problem	The problems of environment, such as noise, illumination, humidity, and toxic gas content

7.1.4. Process

The process category, also known as the technical process, refers to essential techniques or phases during the construction process, but does not include the building operation performed by workers.

Table 7-5. Contributors within the process category to construction occupational accidents

Contributor	Definition/explanation
Design deficiency/defect	Inaccurate or insufficient details of the design document, including mechanical analysis and design for the structure, equipment, tools, materials and the work site
Inadequate method statement	Ambiguous, incomplete, or incorrect work method statement that specifies the procedure of a task

Insufficient test	Missed or incorrect equipment, material, structure, or environment tests for revealing flaws or defects
Irregular working hours (work shift / overtime)	Irregular working hours, like overtime, night shift, and working on holiday, which may lead to disturbances in physiological and psychological conditions
Supply/housekeeping problem (housekeeping)	Inefficient supply and maintenance, which may cause problems with the lack of function of materials, equipment, machine, PPE, or working conditions on the construction site

7.1.5. Organization

The organization category refers to the organization environment.

Table 7-6. Contributors within the organization category to construction occupational accidents

Contributor	Definition/explanation
manpower allocation problem	Allocate the task to incompetent subcontractors or unqualified workers, or the subcontract/task is not clearly defined
Insufficient management rule	Ambiguous, incomplete, or incorrect working rules, unclear roles and duties of workers, unclear distribution of responsibility, and poor management of the team
Insufficient safety training	Missing or inadequate safety training due to incomplete, ambiguous, incorrect content or insufficient training time, which causes poor knowledge or awareness of safety
Schedule pressure	High expectation of construction time, which may lead to modification of project design, resource supply, manpower allocation, etc.
Economic pressure	Budget reduction or overspending, which may lead to tight project design, resource supply, manpower allocation, etc.

7.1.6. No Supervision/Inspection Included

Supervision, also known as inspection, plays a vital role in the construction industry. Supervision is required in most construction sectors, including materials, structure, process, working rules, working plan, financial issues, and timetable. However, supervision or inspection is usually conducted by a separate professional team instead of the contractor. In other words, it is like a monitor or a safeguard running by a third party. Thus, the supervision/inspection is excluded in this classification scheme.

7.2. Dataset of Construction Occupational Accidents in China

7.2.1. Data Collection

A dataset with sufficient data is required to establish causal links between contributors and occupational accidents. In this study, we collected over 3000 accident reports, including occupational accidents and structural failure, from dozens of local authorities, insurance companies and construction firms in China, including mainland China and Hong Kong SAR. However, many reports lack sufficient detail, especially those about non-fatal cases. For example, in an incident report of a fall from height, the cause was simply specified as "careless", but no further information, such as workplace, the worker's characteristics, training, or safety rules, is included. Thus, these reports were excluded, leaving only 303 reports about fatal accidents or severe structural failure with sufficient details in the data analysis.

7.2.2. Data Classification

To demonstrate how data classification works with the detailed description of an accident report, a gas explosion accident during the construction of the Dongjiashan tunnel in Sichuan, China, was used as an example (see Table 7-7**)**. The Dongjiashan tunnel was part of a highway from Dujiangyan to Wenchuan in Sichuan province in the southwest of China. The accident occurred on December 22, 2005, which caused 44 fatalities, 11 injuries, and a direct economic loss of 20.35 million RMB (about 2.6 million Euros). The tragedy was triggered by a plug short circuit and a high concentration of gas. The investigation report revealed no further information about the short circuit, but elaborated on the high gas concentration at the construction site. According to the report, high gas concentration was related to a ventilation system problem that had been found a few days but not yet resolved, so fresh air had not been sent to the tunnel for a while. Additionally, the gas concentration inspection was not properly performed due to unskilled workers. Furthermore, designers underestimated the danger of gas content and no precautious measures or technical procedures for gas leakage were implemented.

Table 7-7. Classification and interpretation of nodes for modelling Dongjiashan tunnel accident

Category	Contributor	Justification*
Occupational accident		There were 44 fatalities, 11 injuries.
Structure failure		The working face of tunnel collapsed.
Human	Wrong action	Workers failed to fill the inspection form properly.
	Insufficient skill	The workers to monitor gas concentration were unqualified. They did not have sufficient knowledge to conduct the inspection and fill the form.
Resource	Machinery problem	An ignition source triggered the explosion due to the short circuit of a plug within an electric cabinet. The ventilation system had been out of work for a few days.
Workplace	Site environment problem	A previous supervision report indicated a few days earlier that there was insufficient fresh air and luminance in the tunnel. No improvement had been reported before the accident occurred.
Process	Design deficiency	Designers underestimated the danger of the gas content. No precautions or technical method for gas leakage were mentioned in any of the design documents. Only the gas concentration monitoring rules were specified.
	Insufficient test	Some data required by the gas test form were missing. The frequency of tests did not meet the standard.
Organization	Supply /maintenance problem	The ventilation system problem had been reported, but it was not fixed.
	Manpower allocation problem	The allocation of manpower was improper or inadequate, such as using an unqualified gas monitoring team.

* *Inferred from descriptions in the accident investigation report on the gas explosion at the construction site of the Dongjiashan tunnel.*

This example demonstrated how irregular information was classified through qualitative analysis of accident reports. However, such an analysis could only reveal whether a problem existed but could not measure its severity. Therefore, in the dataset, all factors were specified as two states, which are irregular and regular, in other words, whether a problem existed or not. The dataset has been named the Contributors to Construction Occupational Accidents Dataset (CCOAD) (see Appendix D).

7.2.3. Results of Data Classification

Table 7-8 summarizes the results of the data classification. The human category was identified in 77.89% of accident cases, with 71.95% being wrong action. Insufficient skill and poor safety knowledge were approximately 30%, which played an important role in construction safety performance. PPE failure (12.54%), machine problem (17.16%) and insufficient site layout (14.19%) were the main contributors in the resource category (30.69%) and the workplace category (23.10%). The failure of the process appeared in 71.62% of the cases, including inadequate method statements (33.33%), design deficiency (29.04%), and supply/maintenance problems (18.48%). Organizational issues accounted for 34.32%, with an essential role in the allocation of manpower (20.46%).

Table 7-8. Results of data classification

Node	Frequency*		Category	Frequency*	
	#	%		#	%
occupational accident	296	97.69			
structure component failure	120	39.60			
Wrong action	218	71.95	Human	236	77.89
Physical problem	7	2.31			
Insufficient skill	91	30.03			
Poor safety knowledge	97	32.01			
Communication failure	18	5.94			
PPE failure	38	12.54	Resource	93	30.69
Machinery problem	52	17.16			
Material deficiency	15	4.95			
Site layout problem	43	14.19	Workplace	70	23.10
Site environment problem	31	10.23			
Design deficiency	88	29.04	Process	217	71.62
Inadequate method statement	101	33.33			

Insufficient test	42	13.86			
Irregular working hours	5	1.65			
Supply/ maintenance problem	56	18.48			
Manpower allocation problem	62	20.46	Organization	104	34.32
Insufficient management rule	24	7.92			
Insufficient safety training	20	6.60			
Schedule pressure	16	5.28			
Economic pressure	8	2.64			

** Number of events in which contributors appeared*

7.3. Dependence Analysis

Expert evaluation method and independence test were combined to identify dependency links.

7.3.1. Relation Table

A questionnaire was developed to build the relation table of contributors. A relation table was then filled with weights indicating the dependence's strength. Table 7-9 shows an example of a relation table. The entire table can be found in Appendix C.

Table 7-9. An example of a relation table of contributors built from the questionnaire

Consequence / Contributor	Occupation accident	Structure failure	Wrong action	Physical problem	Insufficient skill	Poor safety knowledge
Occupation accident						
Structure failure						
Wrong action	3	3		0	0	0
Physical problem	0	0	3		0	0
Insufficient skill	0	0	3	0		0
Poor safety knowledge	0	0	3	0	1	

- Strong-dependence

A score of 3 indicated a strong dependence on experts who judged a contributor to be the cause of a consequence. For example, structural failure is likely to cause occupational accidents.

- Weak-dependence

A score of 1 indicated a weak dependence that experts postulated that a contributor might be a cause of the consequence, but they could not make a strong statement. For example, experts may suspect that a construction schedule or economic pressure might lead to a less optimal method statement.

- Non-dependence

A score of 0 indicated that there was no dependence on whether a contributor was viewed as the cause of a consequence. For example, experts may not believe that insufficient skills could cause physical problems for the worker.

To help fill the table, the following principles were followed:

I. Only direct dependence is qualified to be considered as a strong or weak dependence. Indirect dependence should be classified as non-dependence. For example, insufficient safety training may cause poor safety knowledge that leads to wrong action, but inadequate safety training is not directly related to wrong action.

II. Only human errors from construction workers on site are included in the model, but no other staff and personnel in the organization or the process are included.

III. The hierarchy rule is introduced so that contributors are grouped into four levels, including:

First level: Organization group

Second level: Process group

Third level: Worker group, Resource group, Working site group

Fourth level: Structure failure, Occupational accident

7.3.2. Questionnaire

Five experts were invited to complete the questionnaire. Two of them were site managers of contractors, another two were on-site chief supervisors, and one was from academia. All experts had more than 20 years of experience in construction management. The questionnaire (see Appendix C), the taxonomy, the definition (from Table 7-1 to Table 7-6), and the statistical analysis results (Table 7-8) were provided to experts. The experts filled the forms independently.

For each box in the form, when the score was no less than 9, standing for three strong dependencies or two strong dependencies and three weak dependencies at least, suggesting that at least half of the experts believed that the dependence existed. Thus, the dependence relation was included in the model. The dependence relation was excluded from the model when the score was no more than 6, which is for two strong dependency links at most. A further independence test has been done for cells with a dependency score of 7 or 8. Table 7-11 shows the summary results of the questionnaire. Overall, 42 dependence relations have been built, with four more requiring further analysis (highlighted in the table). The forms filled out by the five experts can be found in Appendix C.

7.3.2. Independence Test

Since all nodes are binary variables with two states, the Chi-square test was used to analyze the independence following the procedure of the Chi-square test in Section 2.3.2. Table 7-10 shows the results of the Chi-square test.

Table 7-10. Results of the Chi-square test for independence

Target factors	Test statistic	Conclusion for dependence
Inadequate method statement & insufficient skills	0.7624	independent

Scheduling pressure & manpower allocation problem	31.1358	dependent
Site layout & occupational accident	428.5512	dependent
Site environment & wrong action	238.3901	dependent

According to Table 2-5, the dependence probability of the first pair is less than 75%, while others are as high as more than 99.9%. Thus, the last three pairs were considered to hold dependent relations. In total, 45 dependencies were identified in the model.

Table 7-11. Summary of the questionnaire

contributor \ consequence	occupation accident	structure failure	wrong action	physical problem	insufficient skill	poor safety awareness	communication failure	PPE failure	equipment/tools deficiency	material deficiency	site layout	site environment	design deficiency	inadequate method statement	insufficient test	Irregular working hours	supply /maintenance problem	manpower allocation problem	insufficient management rule	insufficient safety training	scheduling pressure	economic pressure
occupation accident																						
structure failure	15																					
wrong action	15	13		0	0	0	0	0	0	0	0	0										
physical problem	0	0	15		0	0	4	0	0	0	0	0										
insufficient skill	0	0	15	0		1	1	6	0	0	0	0										
poor safety awareness	0	0	15	0	1		5	15	0	0	0	0										
communication failure	1	0	15	0	0	3		1	0	0	0	3										
PPE failure	15	0	0	0	0	0	0		0	0	0	0										
equipment/tools deficiency	15	5	0	0	0	0	0	0		0	0	0										
material deficiency	2	15	0	0	0	0	0	0	4		0	0										
site layout	8	0	0	0	0	0	1	0	0	0		0										
site environment	0	0	8	5	0	0	15	0	0	0	0											
design deficiency	0	15	0	0	0	0	0	1	15	15	15	4		15	0	0	0					
inadequate method statement	0	3	15	0	7	0	0	0	0	0	3	0	0		4	0	0					
insufficient test	0	15	0	0	0	0	0	3	15	15	0	15	0	0		0	0					
Irregular working hours	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0		0					
supply/ maintenance problem	0	0	0	0	0	0	0	15	15	15	12	15	0	0	0	0						
manpower allocation problem	0	0	0	6	15	11	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0
insufficient management rule	0	0	3	0	3	0	15	0	0	0	4	0	3	10	15	0	15	15		15	0	0
insufficient safety training	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0
schedule pressure	0	0	2	2	0	0	0	0	0	0	2	0	15	5	3	15	6	8	1	1		0
economic pressure	0	0	0	0	0	0	0	0	0	0	2	0	10	5	3	0	15	15	0	0	0	

7.4. BN Model for Contributors to Construction Occupational Accidents

7.4.1. Network Structure

Figure 7-1 shows a causal graph representing the structure converted from the questionnaire and the independence test. This graph illustrates the contributors to accidents and their dependency links. Nodes from different groups were shown in distant background colours.

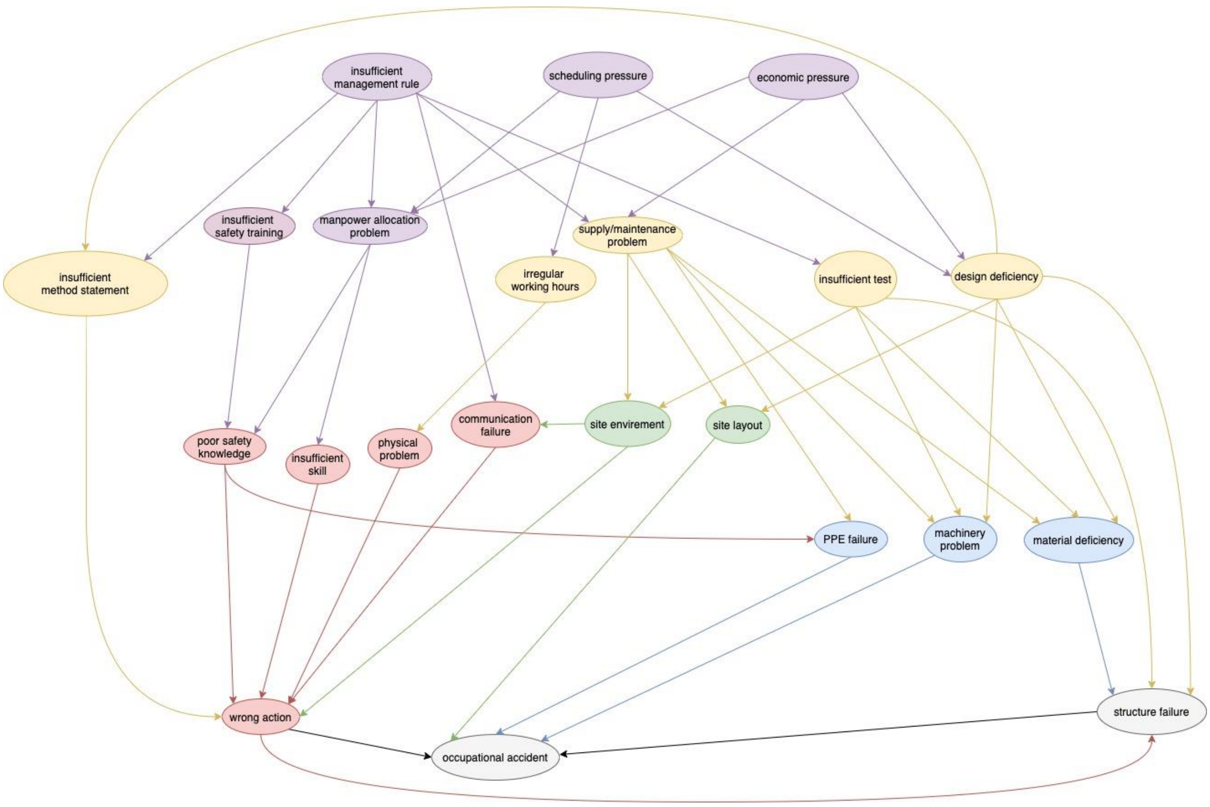


Figure 7-1. Structure of a BN model for contributors to construction occupational accidents

7.4.2. Conditional Probability Table

The parameter learning process followed the belief propagation algorithm provided by Bayesian Network Toolbox within Matlab (Murphy, 2003) using all data. A uniform distribution was given as a prior probability for all nodes to aid in parameter learning.

7.4.3. Model Validity

Our model may have some limitations. First, since the network parameter was updated from the dataset, the robustness is based on the quality of the dataset. However, since the network structure presented in this chapter was developed according to expert knowledge and an independence test subsequently, the structure is believed to fit empirical knowledge and the dataset. Second, since most of the data were adapted from accident reports, the probability value of a regular state for accidents is highly underestimated compared with the real world. When this model is used to examine contributors in a construction accident, it is reliable. However, this model cannot be used to predict the probability distribution of accidents, but to diagnose the frequency and probability of causes.

7.5. Analysis of Contributors to Construction Occupational Accidents

The analysis focuses on three nodes: occupational accident, structure failure, and wrong action. The first two are types of construction accidents, while the last is a typical human error performance. These three nodes were treated separately as consequences during the inference calculation. The calculation process was executed with Pearl's belief propagation algorithm provided by Bayesian Network Toolbox within Matlab (Murphy, 2003).

7.5.1. Main Paths to Occupational Accidents in the Construction Industry

A diagnostic analysis was first conducted to locate possible contributors to accidents. Based on the assumption that the accident was in an irregular state, the irregular probability of each contributor was then calculated. Figure 7-2 shows the result.

Wrong action contributed the most to the occurrence of accidents compared to other contributors, suggesting that wrong behaviours of workers caused the majority of occupational accidents in the construction industry in China. In other words, human error is the most frequent trigger of accidents. The second possible contributor is structure failure, representing another major trigger of accidents. Problems in method statements and safety knowledge accounted for more than 30% of accidents, followed by skills, design, and allocation of manpower, with probabilities around 20% and 30%, respectively.

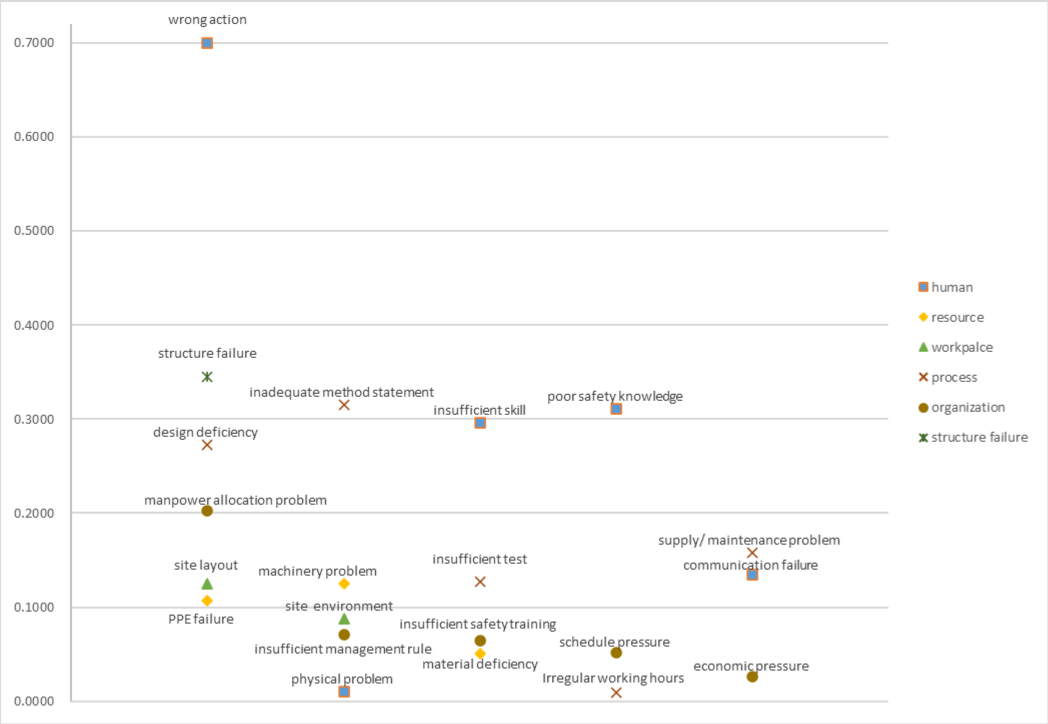


Figure 7-2. Probability of contributors to the occurrence of occupational accidents in the construction industry

To identify the main paths between contributors to accidents, the diagnosis results of all probabilities about irregular states were added to the causal model graph (see Figure 7-3). Figure 7-3 indicates several main paths between contributors to accidents, but contributors in the human category had higher probabilities of causing accidents than other contributors. The accidents had five parents, with the wrong action having the highest probability, followed by structural failure. Among the six parents of the wrong action, the probability of inadequate method statement, poor safety knowledge, and insufficient skill had higher probabilities than other contributors. The inadequate method statement could be caused by design deficiency and insufficient management rule. The insufficient management rule was more related to the manpower allocation problem than its other two parents. Manpower allocation problem was the only parent of insufficient skill, and it was more likely than insufficient training problem to cause poor safety knowledge.

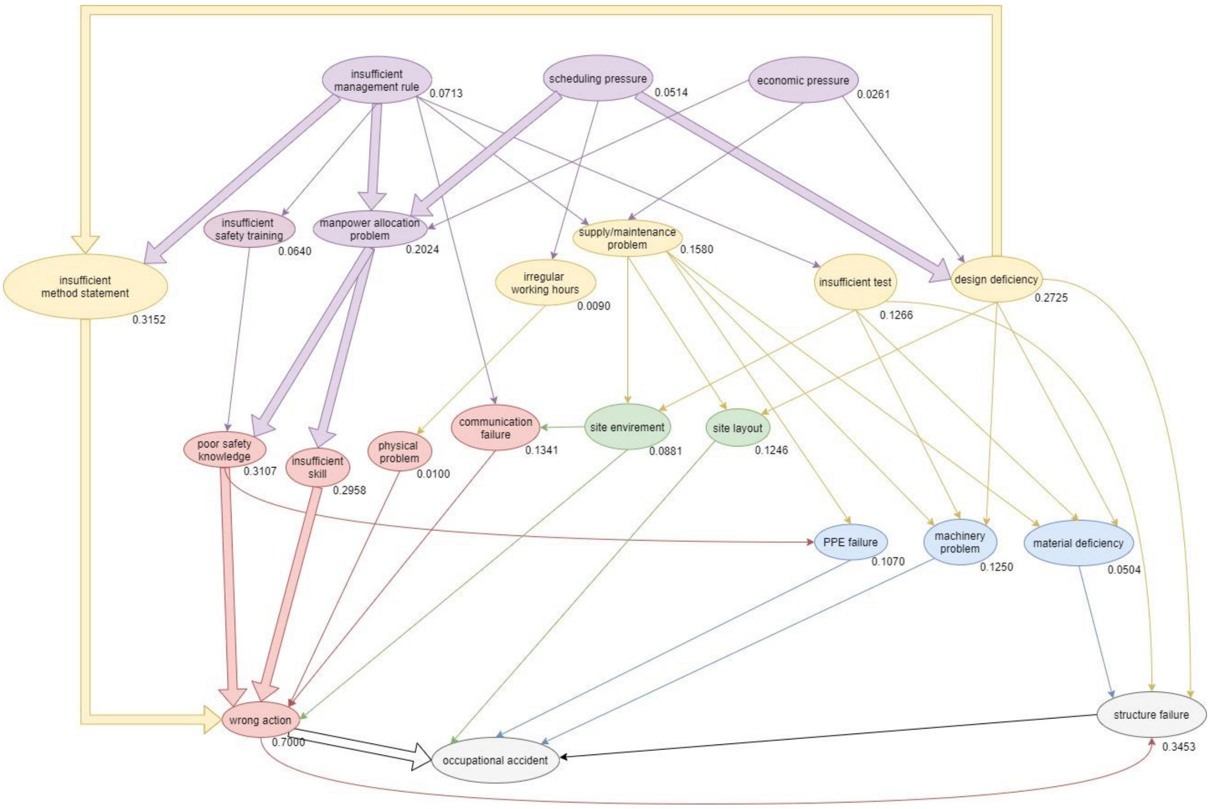


Figure 7-3. Main paths to occupational accident

7.5.2. Main Contributors to Structure Failure

As structural failure also had a high probability of causing accidents, we examined the main contributors to structural failure. Given a structural failure with an unknown state of the accident node, we calculated the irregular probabilities of the parents and ancestors of structural failure. Figure 7-4 shows the results.

The probability of wrong action was around 70%, the highest among all contributors. According to Figure 7-4, design deficiency was another frequent cause of structural failure. The probabilities of inadequate method statement, insufficient skill, and poor safety knowledge behind structural failure were around 30%. Their probabilities were much higher than those of other contributors except for wrong action and design deficiency.

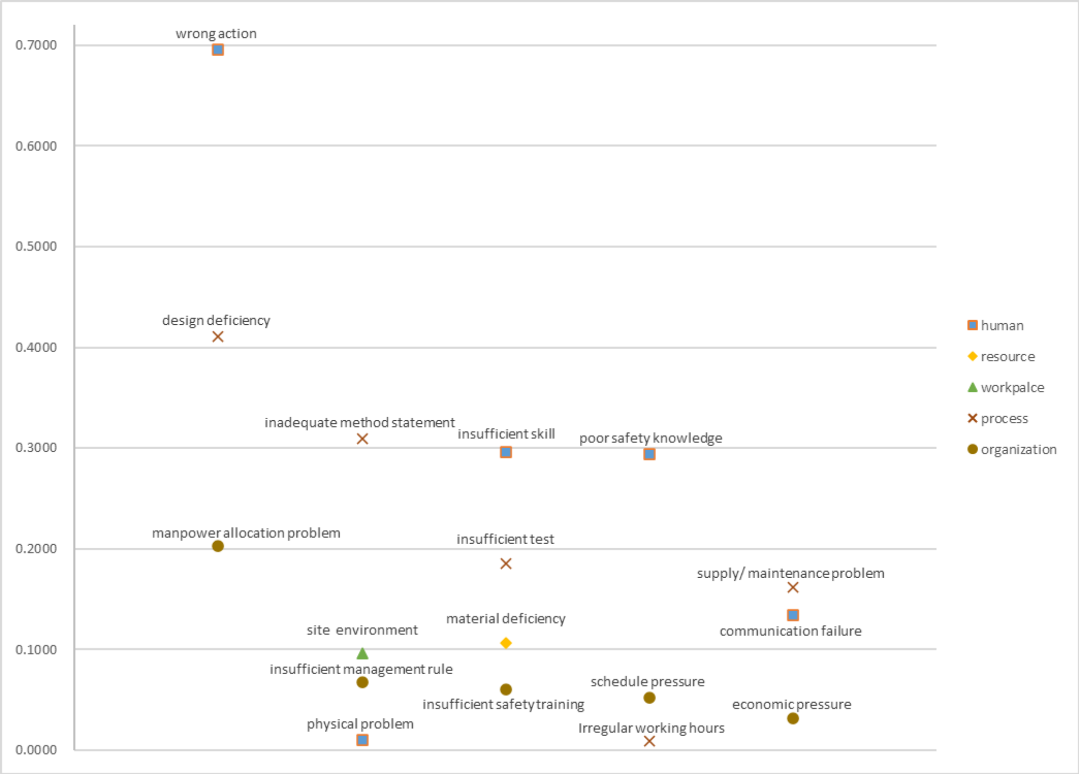


Figure 7-4. Contributors to structure failure

7.5.3. Triggers to Cause Wrong Action

The contributors to the wrong action (the state was irregular) were further examined in the model. The probabilities of its parents and ancestors were then calculated. Figure 7-5 shows that insufficient skill, poor safety knowledge, inadequate method statement, design deficiency, as well as manpower allocation problem were among the leading contributors to the wrong action. Figure 7-6 shows the main paths to wrong action and five contributors to human errors, including method statement, design quality, manpower allocation, management rule, and scheduling.

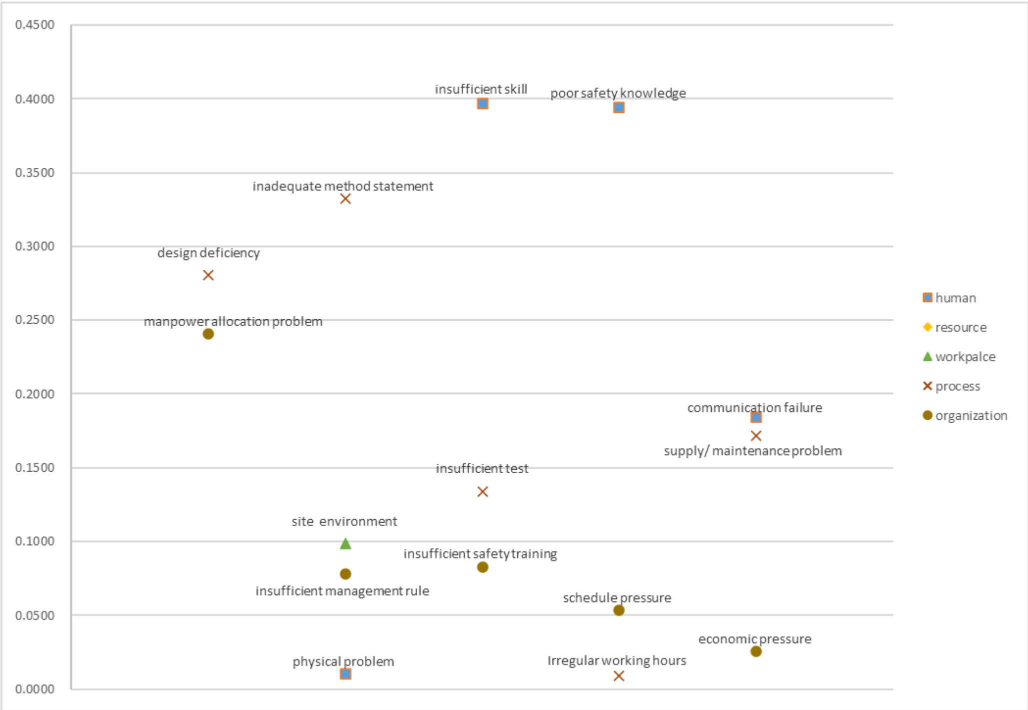


Figure 7-5. Contributors to wrong action

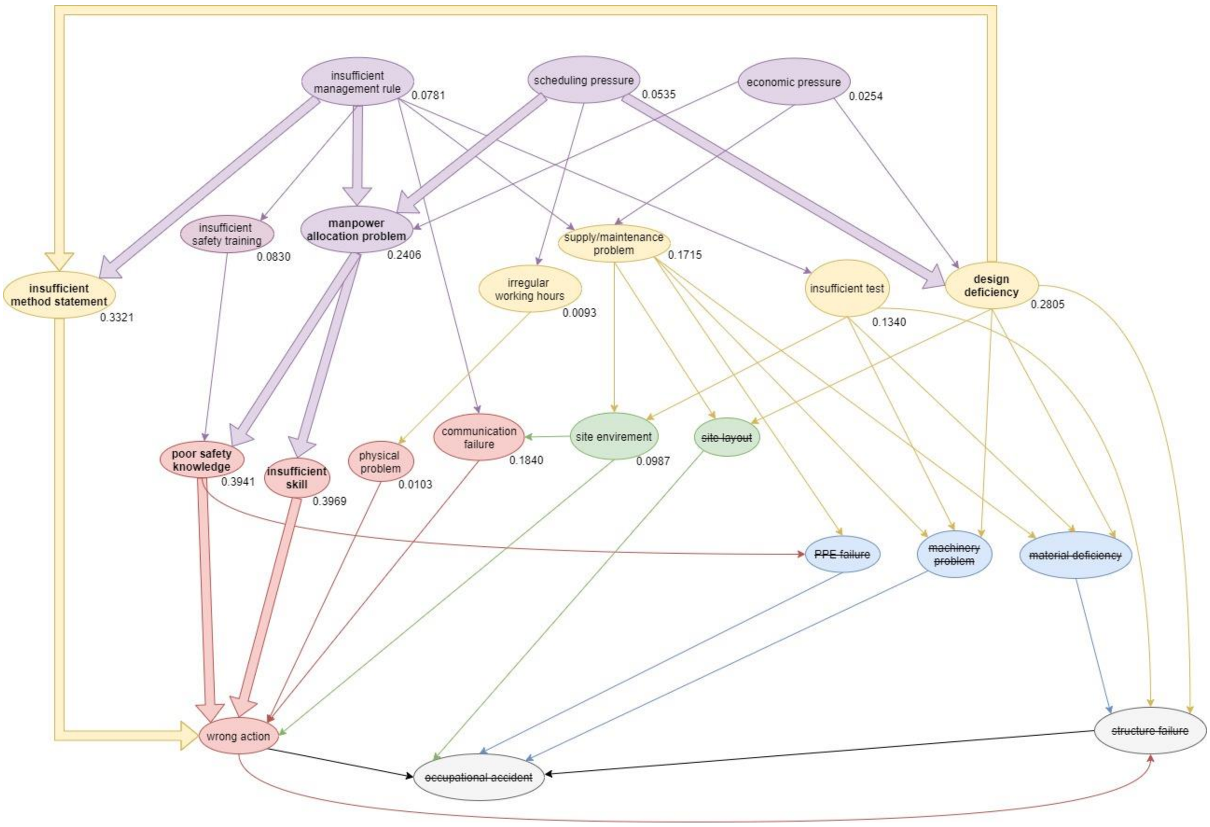


Figure 7-6. Main Paths to the wrong action

The influence weight of each contributor in the main path to wrong action was then calculated. The variation of the child node was measured when each contributor node was in the opposite state. According to Section 5.4.2, the process was expressed as following:

$$\text{Weight (contributor} \rightarrow \text{wrong action)} = \frac{[\mathit{Probability}(\text{action} = \text{I}|\text{contributor} = \text{I}) - \mathit{Probability}(\text{action} = \text{I}|\text{contributor} = \text{R})]}{\mathit{Probability}(\text{action} = \text{I}|\text{contributor} = \text{R})}$$

Figure 7-7 shows that insufficient skill and poor safety knowledge were the two main contributors to wrong action, followed by the problem of manpower allocation and insufficient management rules. On the contrary, design deficiency did not play a significant role in wrong action. Figure 7-8 shows the most significant paths in red.

To mitigate the influence of human error to decrease the wrong action of workers in construction, the probabilities of contributing human errors should be reduced. However, there should be a priority due to the limited financial and time costs. As shown in Figure 7-7, the nodes on the red path should be dealt with first, and then the nodes on other highlighted paths should be checked.

Table 7-12 shows a summary of these paths. Level 1 should be the path that requires close attention.

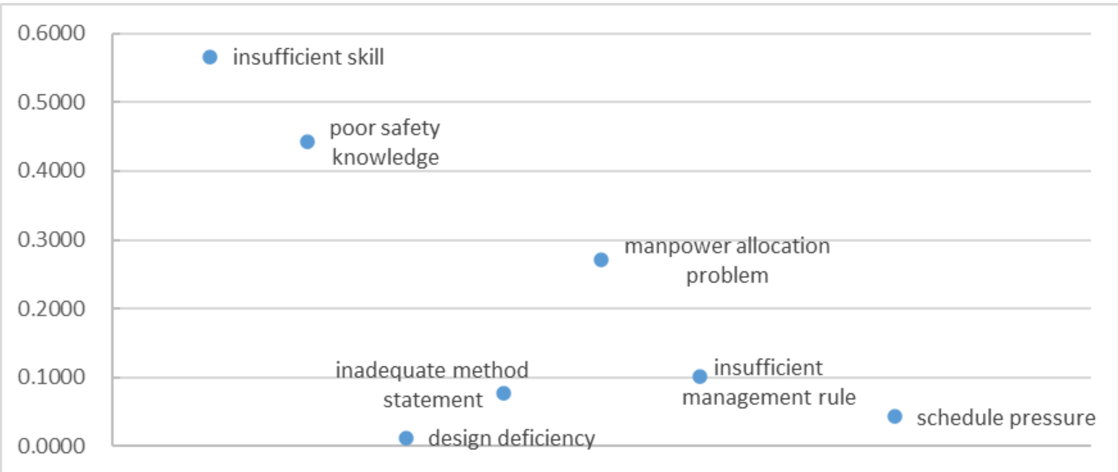


Figure 7-7. Weight of contributors to wrong action

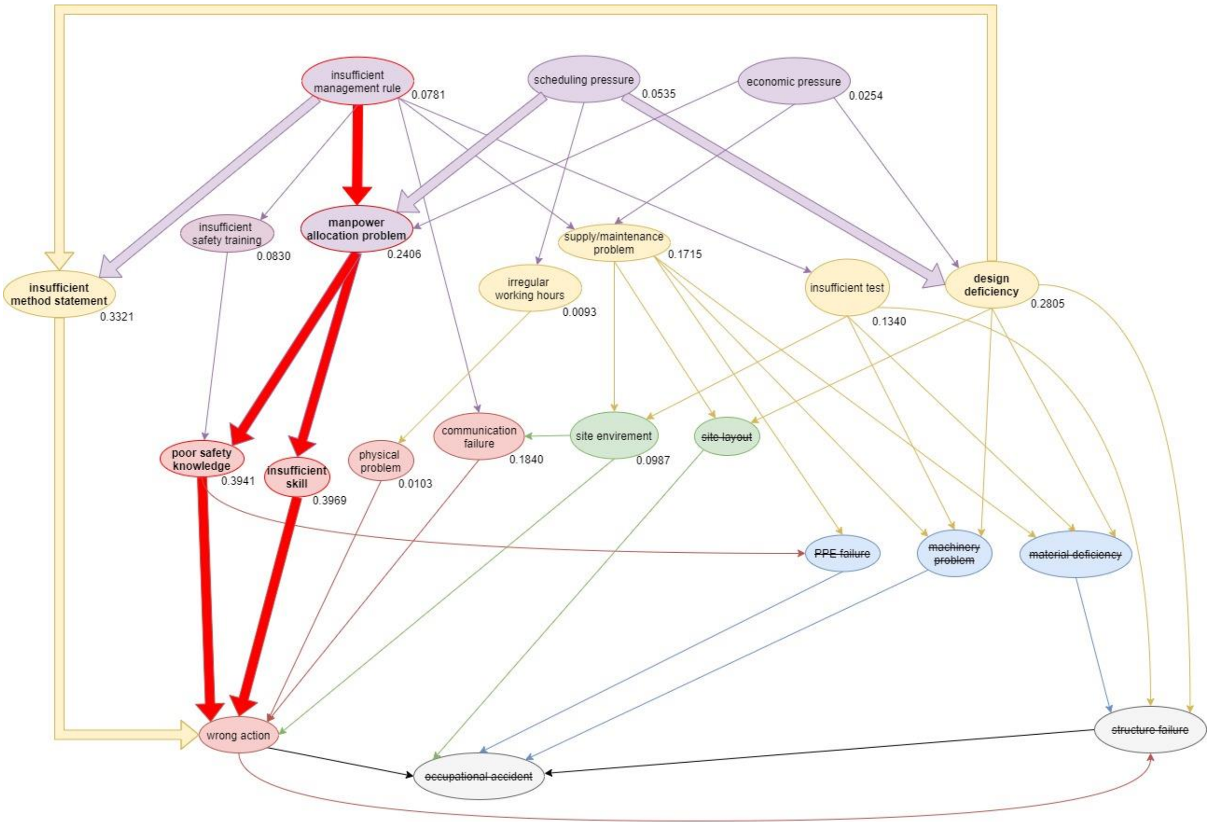


Figure 7-8. Most significant paths to wrong action

Table 7-12. Suggested levels to mitigate wrong action in construction

	Paths to wrong action
Level 1	Insufficient management rule → manpower allocation problem → Poor safety knowledge Insufficient management rule → manpower allocation problem → Insufficient skill
Level 2	Insufficient management rule → Insufficient method statement Schedule pressure → Design deficiency → Insufficient method statement
Level 3	Other paths are shown in Figure 7-8

7.6. Conclusion

To conclude, we show that human error was the main contributor to accidents in the construction industry in China. However, it should be noted that our dataset has some limitations. This dataset only included accidents (irregular cases) in the construction industry, most of which were occupational accidents. Thus, the nature of the data influenced the results of the analysis. In daily work of industry, some of the irregular contributors may not cause any accidents, neither occupational accident nor structure failure. Unfortunately, such cases were not collected to this dataset. Therefore, in the CPT developed from such dataset, the regular probability value for the consequent node, given irregular states of parent(s), may be highly underestimated. This limitation may exaggerate the weight influence of contributors to accidents. This is also the reason why the weights of contributors to the accident were not calculated.

Furthermore, the frequency of irregular cases (with every node) reported in Section 7.5 is no doubt higher than in the real world due to the lack of data for regular cases. However, it still shows the pattern representing which contributors had higher probabilities than others. More data, especially regular examination reports, are required to improve the model. The value within CPT could also be modified using statistical or empirical knowledge.

Chapter 8. Conclusion

8.1. Summary and Contributions

This dissertation developed accident causal models based on Bayesian Network (BN) for the Human Performance Separated System (HPSS) and the Human Performance Included System (HPIS). It examined the influence of human perception in HPSS and human error in HPIS based on BN modelling. This dissertation made several empirical and theoretical contributions.

First, we proposed new approaches to explore the causes of accidents, including:

1）We classified systems into two types, HPSS and HPIS, depending on whether the system involves human performance. HPSS is a hardware system, while HPIS is more complex and influenced by human performance related to management, process, site environment, etc.

2）We specified a taxonomy for the HPIS failure assessment model, which was used for data collection and BN modelling. We further developed a Contributors Taxonomy for Construction Occupational Accidents.

3）We examined two methods for the analysis of human error. The first method was based on the cognitive view, with the aim of finding the influence of contributors related to human cognition that led to wrong action. The other method focused on the role of human error within the HPIS failure model by treating human action as an essential part of the system.

Second, we introduced several strategies for the modelling process, including:

1）We proposed a method to combine expert judgement and data analysis to specify the BN structure. For a specific industry sector, we suggested that the expert evaluation method first identify the main dependency links. Mathematical independence analysis should then examine the rest of the nodes.

2） We suggested that the influence of human perception on the model parameter should be measured when the parameter was identified based on expert judgement.

Third, to demonstrate the practical use of the above suggestions, we developed models that could be applied to systems in different industrial sectors. They were used as examples of the proposed methodology. These models also explored the quantitative relations of accidents in these systems.

1） The gas turbine failure model was a typical example of machine failure in HPSS. We revealed that human perception was significant positive correlated with model parameters, as indicated by model output results.
2） Using the Multi-Attribute Technological Accidents Dataset (MATA-D), we weighted the impact of contributors to the cognition process behind human error in accidents.
3） We further proposed a model to examine occupational accidents in the construction industry based on the Contributors to Construction Occupational Accidents Dataset (CCOAD). This model aimed to examine complex HPIS systems. We identified the main paths to occupational accidents in the construction industry and further quantified the contributors to structural failure and wrong action that were direct triggers of accidents.
4） The CCOAD can be used as a dataset for further studies and a framework for data collection from similar works.

8.2. Future Research Direction

Further studies can aim to build new models and collect data for other industry fields by following the framework and practical guidelines proposed in this dissertation. In particular, more studies may focus on these areas:

In our study, the human perception analysis in Chapters 3 & 4 was conducted in a way that was similar to parameter sensitivity analysis because we examined the influence of expert judgements using predetermined parameters. Future studies may explore human perception in other tasks, including taxonomy development and dependency analysis.

Regarding human error in the HPIS, we have focused only on-site workers. Future studies may examine human error at other stages of construction, including design, planning, and decision-making.

We defined the nodes as binary, speaking regular and irregular situations. However, the node could be more complicated in the real world. For example, human skills could have more sophisticated levels of measurement. Similarly, the speed and temperature of the system could be used as continuous variables. Thus, future studies may include these factors as continuous variables, but not binary variables.

Both datasets in Chapters 6 & 7 were developed based on accident reports and thus limited the use of the models. As the regular operation of a system is supposed to be more frequent than the occurrence of an accident, the corresponding models cannot reveal the whole picture and are likely to be reliable only when accidents occur. Future studies may focus on predictive analysis of accidents by including both regular and irregular data.

The results of Pearson's Chi-square Test, mentioned in Section 2.3.2.3, showed the probabilities of the dependence of the nodes. Then, expert judgement was used to determine whether the nodes were dependent or not. One potential problem is the lack of criteria to achieve this cut-off point. However, this problem can be found in other algorithms regardless of whether the statistical analysis was used individually or as a supplement to the expert judgement. Future studies may aim to address this issue.

Furthermore, future studies may work on collecting more data. Theoretically, we may overcome all the limitations mentioned above with sufficient data. Practical guidelines are required and play a crucial role in the taxonomy of data collection. Moreover, although the taxonomy blueprints are good examples, more data is needed to further improve the taxonomy.

In conclusion, this dissertation makes important theoretical and empirical contributions to modelling accident causation for HPSS and HPIS based on Bayesian Network (BN). The modelling of HPSS failure relied mainly on expert judgement only, while the modelling of HPIS failure combined expert judgement and statistical analysis. For the HPSS failure model, we analysed the influence of human perception on the model. With the HPIS failure model, we suggested exploring human errors from a cognitive point of view in the industry while treating the human factor as a core part of HPIS in a specific domain. Importantly, we developed a BN model based on a dataset that collects 303 accidents in Chinese construction industry. Our model is an important example for analysing the direct and indirect influence of contributors to accidents. However, future studies may further improve these models by using larger datasets with numerical variables instead of binary variables as contributors.

Bibliography

Aguilar, O., and M. West. 2000, 'Bayesian dynamic factor models and portfolio allocation'. *Journal of Business & Economic Statistics* 18(3): 338–57.

Ahn et al. 2021. 'Accident cause factor of fires and explosions in tanks utilizing fault tree analysis' *Journal of Marine Science and Engineering* 9(8): 844.

Allan Gut. 2013. Probability: A Graduate Course *Probability: A Graduate Course 2nd Ed*. Springer New York.

Bayes server, LLC. 2019. 'Tutorial 8 of Bayes Server- Structural Learning.'https://www.bayesserver.com/docs/walkthroughs/walkthrough-8-structural-learning (June 13, 2022).

BayesFusion, LLC. 2019. *GeNIe Modeler User Manual*. https://www.bayesfusion.com/ (June 13, 2019).

Blanco, Rosa. 2005, 'Learning Bayesian Networks from Data with Factorisation and Classification Purposes. Applications in Biomedicine."

Bona, Gianpaolo di, Domenico Falcone, Antonio Forcina, and Luca Silvestri. 2021. 'Systematic Human Reliability Analysis (SHRA): A New Approach to Evaluate Human Error Probability (HEP) in a Nuclear Plant.'*International Journal of Mathematical, Engineering and Management Sciences* 6(1): 345–62.

Bruce Hallbert, INL Alan Kolaczkowski, and Erasmia Lois. 2007. *The Employment of Empirical Data and Bayesian Methods in Human Reliability Analysis: A Feasibility Study.*

Budiyanto, Muhammad Arif, and Haris Fernanda. 2020, 'Risk assessment of work accidents in container terminals using the fault tree analysis method'. *Journal of Marine Science and Engineering 2020, Vol. 8, Page 466* 8(6): 466.

Chen, Shuai, Li Zhang, Tao Qing, and Xueyang Liu. 2021. 'Use of Bayesian networks and improved SPAR-H for quantitative analysis of human reliability during the sever accident mitigation process in nuclear power plant'. *Journal of Nuclear Science and Technology* 58(10): 1099–1112. https://www.tandfonline.com/doi/abs/10.1080/00223131.2021.1915893 (June 8, 2022).

Choi, Eun-Bi, and Dong-Han Ham. 2020. 'A FRAM-Based Systemic Investigation of a Rail Accident involving Human Errors' *Journal of the Korea Safety*

Management & Science 22(1): 23–32. http://dx.doi.org/10.12812/ksms.2020.22.1.023 (June 8, 2022).

Constantinou, Anthony Costa, Norman Fenton, and Martin Neil. 2016. 'Integrating Expert Knowledge with Data in Bayesian Networks: Preserving Data-Driven Expectations When Expert Variables Remain Unobserved ' *Expert Systems with Applications* 56: 197–208.

Cooper, Gfc, Gregory, F. 1992, 'A Bayesian Method for the Induction of Probabilistic Networks from Data'. 9: 309–47.

Darwiche, Adnan. 2009. *Modeling and Reasoning with Bayesian Networks*. Cambridge University Press.

David J. Hand, Heikki Mannila, and Padhraic Smyth. 2001. *Principles of Data Mining | The MIT Press*. MIT Press. https://mitpress.mit.edu/books/principles-data-mining (June 15, 2022).

David, Lida Z., Jan Maarten Schraagen, and Maaike Endedijk. 2022. 'Toward the incorporation of Temporal Interaction Analysis Techniques in Modeling and Understanding Sociotechnical Systems'. *Human Factors and Ergonomics in Manufacturing & Service Industries* 32(1): 35–49. https://onlinelibrary.wiley.com/doi/full/10.1002/hfm.20930 (June 8, 2022).

Diop, Issa, Georges Abdul-Nour, and Dragan Komljenovic. 2022. 'The Functional Resonance Analysis Method: A Performance Appraisal Tool for Risk Assessment and Accident Investigation in Complex and Dynamic Socio-Technical Systems.'*American Journal of Industrial and Business Management* 12(02): 195–230.

Dsouza, N., & Lu, L. (2017). A Literature Review on Human Reliability Analysis Techniques Applied for Probabilistic Risk Assessment in the Nuclear Industry. *Advances in Human Factors in Energy: Oil, Gas, Nuclear and Electric Power Industries*, 41–54. https://doi.org/10.1007/978-3-319-41950-3_4.

Dwi Wicaksono, Fermi et al. 2022. 'A State of the Art of Accident Causation Models in Process Industries' *Process Safety Progress* 41(1): 167–76. https://onlinelibrary.wiley.com/doi/full/10.1002/prs.12283 (June 8, 2022).

E. Scott Dunlap, Bryan Basford, and Michelle L. DePoy Smith. 2019. 'Remodeling Heinrich: An Application for Modern Safety Management | Professional Safety | OnePetro. ' *professionary safety* 64(5): 44–52. https://onepetro.org/PS/article-abstract/64/05/44/33595/Remodeling-Heinrich-An-Application-for-Modern?redirectedFrom=fulltext (June 8, 2022).

E.A. Rosa, David Embrey, Patrick Christie Humphreys, and D.E. Embrey. 1985. *SLIM-MAUD: An Approach to Assessing Human Error Probabilities Using Structured Expert Judgement. Volume I. Overview of SLIM-MAUD*. Upton, NY (USA): Brookhaven National Lab. https://www.nrc.gov/docs/ML1031/ML103140237.pdf (June 8, 2022).

Erik Hollnagel. 1998. *Cognitive Reliability and Error Analysis Method*. Elsevier Science Ltd. http://www.elsevier.nl.

Erik Hollnagel. 2012a. 'CREAM-Cognitive Reliability and Error Analysis Method'. https://erikhollnagel.com/ideas/cream.html (July 21, 2022).

Erik Hollnagel. 2012b. 'The Functional Resonance Analysis Method (FRAM).' https://www.functionalresonance.com/ (July 21, 2022).

Farcasiu, M., and C. Constantinescu. 2021. 'Evaluation of Human Factor Engineering Influence in Nuclear Safety Using Probabilistic Safety Assessment Techniques.' *Kerntechnik* 86(6): 470–77. https://www.scienceopen.com/document?vid=65f4231c-f9df-4352-9899-63a07c859caf (June 8, 2022).

Federal Institute for Occupational Safety and Health (BauA). 2022. 'Fatal work accidents-Collecting, Interpreting, and Analysing Accident Data'. https://www.baua.de/EN/Topics/The-changing-world-of-work-and-occupational-safety-and-health/Monitoring-working-conditions/Fatal-work-accidents/Fatal-work-accidents_node.html (July 19, 2022).

Finn V. Jensen, and Thomas D. Nielsen. 2007. *Bayesian Networks and Decision Graphs*.

Fu, Gui et al. 2020. 'The Development History of Accident Causation Models in the past 100 Years: 24Model, a More Modern Accident Causation Model'. *Process Safety and Environmental Protection* 134: 47–82.

Gao, Xianghao, Xiaoyan Su, Hong Qian, and Xiaolei Pan. 2022. 'Dependence Assessment in Human Reliability Analysis under Uncertain and Dynamic Situations.' *Nuclear Engineering and Technology* 54(3): 948–58.

Gao, Xiao guang et al. 2019. 'Learning Bayesian Network Parameters via Minimax Algorithm.'*International Journal of Approximate Reasoning* 108: 62–75.

Gattuso, Alexandra. 2021. *Common Issues of Compliance with Personal Protective Equipment for Construction Workers*.

https://digitalcommons.calpoly.edu/cgi/viewcontent.cgi?article=1475&context=cmsp (July 16, 2022).

Gertman, David I. et al. 2004. 'The SPAR H Human Reliability Analysis Method.'*American Nuclear Society 4th International Topical Meeting on Nuclear Plant Instrumentation, Control and Human Machine Interface Technology*: 17–24.

Ghahramani Abolfazl, Adibhesami Abdolnaser, and Mohebbi Iraj. 2020. 'An Application Of Cognitive Reliability Error Analysis Method For Identification And Evaluation Of Human Errors Of Control Room Operators In A Cement Manufacturing Company.'*JOURNAL OF SAFETY PROMOTION AND INJURY PREVENTION* 7(4): 183–91. https://www.sid.ir/en/Journal/ViewPaper.aspx?ID=759932 (June 24, 2022).

K.M. Groth, and A Mosleh. 2009. 'A Data-Informed Model of Performance Shaping Factors and Their Interdependencies for Use in Human Reliability Analysis.'*ESREL Annual Conference, Prague, Czech …*: 231–38. http://www.sandia.gov/~kgroth/publicationfiles/111hermo_ESREL2009.pdf.

Hall, R E, J Fragola, and J Wreathall. 1982. *Post-Event Human Decision Errors: Operator Action Tree/Time Reliability Correlation*. http://www.osti.gov/servlets/purl/6460666/ (June 8, 2022).

Harati-Mokhtari, Abbas, Alan Wall, Philip Brooks, and Jin Wang. 2007. 'Automatic Identification System (AIS): Data Reliability and Human Error Implications.'*The Journal of Navigation* 60(3): 373–89. https://www.cambridge.org/core/journals/journal-of-navigation/article/abs/automatic-identification-system-ais-data-reliability-and-human-error-implications/6664900351CB5D9C3FF45F16D96F8832 (July 19, 2022).

Hasan, Rumy, Christopher Chatwin, and Mustafa Sayed. 2019. 'Examining Alternatives to Traditional Accident Causation Models in the Offshore Oil and Gas Industry.'*Journal of Risk Research* 23(9): 1242–57. https://www.tandfonline.com/doi/abs/10.1080/13669877.2019.1673796 (June 8, 2022).

Heinrich, and Herbert William. 1931. *Industrial Accident Prevention: A Scientific Approach*. New York.

Health and Safety Executive (HSE). 2021. *Manufacturing Statistics in Great Britain, 2021*. https://www.hse.gov.uk/statistics/industry/manufacturing.pdf (June 8, 2022).

ILO. 2022. ‘World Statistic.’https://www.ilo.org/112hermo/areas-of-work/occupational-safety-and-health/WCMS_249278/lang–en/index.htm (June 8, 2022).

Infante, Paulo et al. 2022. ‘Comparison of Statistical and Machine-Learning Models on Road Traffic Accident Severity Classification.’*Computers* 11(5): 80.

Jamshidi, Rasoul. 2020. ‘Developing a New Decision Support System to Manage Human Reliability Based on HEART Method.’*Journal of Optimization in Industrial Engineering* 13(1): 145–52. http://www.qjie.ir/article_666486.html (June 8, 2022).

Joe-Asare, T., N. Amegbey, and E. Stemn. 2020. ‘Human Factor Analysis Framework for Ghana’s Mining Industry.’*Ghana Mining Journal* 20(2): 60–76. https://www.ajol.info/index.php/gm/article/view/202503 (June 8, 2022).

Julie Bell, and Justin Holroyd. 2009. *Review of Human Reliability Assessment Methods*.

Jung, Wondea, and Jinkyun Park. 2020. ‘Time-Reliability Correlation for the Human Reliability Analysis of a Digitalized Main Control Room.’In *Advances in Intelligent Systems and Computing*, Springer, Cham, 88–94. https://link.springer.com/chapter/10.1007/978-3-030-20037-4_8 (June 8, 2022).

Kevin Murphy. 2003. ‘Bayes Net Toolbox for Matlab.’https://github.com/bayesnet/bnt (July 15, 2022).

Kim, Jae Hun, Juyeon Kim, Gunwoo Lee, and Juneyoung Park. 2021. ‘Machine Learning-Based Models for Accident Prediction at a Korean Container Port.’*Sustainability (Switzerland)* 13(16).

Kim, Ji Myong, Kwang Kyun Lim, Sang Guk Yum, and Seunghyun Son. 2022. ‘A Deep Learning Model Development to Predict Safety Accidents for Sustainable Construction: A Case Study of Fall Accidents in South Korea.’*Sustainability (Switzerland)* 14(3).

Kolmogorov, A N, and A T Bharucha-Reid. 1956. *Foundations of the Theory of Probability*.

Koski, Timo., and John M. Noble. 2009. *Bayesian Networks: An Introduction*. John Wiley.

Krymsky, Victor G., and Farit M. Akhmedzhanov. 2021. ‘Assessment of Human Reliability Under the Conditions of Uncertainty: SPAR-H Methodology

Interpreted in Terms of Interval-Valued Probabilities.’*ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering* 7(2).

L. Podofillini, and V.N. Dang. 2017. ‘First Results from an Analysis of Recent Operational Events Involving Errors of Commissions.’In *Safety and Reliability – Theory and Applications*, Taylor & Francis Group, 359–67.

LI Hai-tao et al. 2008. ‘Survey of Bayesian Network Inference Algorithms.’*Systems Engineering and Electronics* 30(5): 935–39. https://www.researchgate.net/publication/289966477_Survey_of_Bayesian_network_inference_algorithms (June 15, 2022).

Li, Qian, Zhe Zhang, and Fei Peng. 2021. ‘Causality-Network-Based Critical Hazard Identification for Railway Accident Prevention: Complex Network-Based Model Development and Comparison.’*Entropy 2021, Vol. 23, Page 864* 23(7): 864. https://www.mdpi.com/1099-4300/23/7/864/htm (June 8, 2022).

Liu, Jianqiao, Liu et al. 2021. ‘Identification of Correlation among Performance Shaping Factors of SPAR-H Method.’*Nuclear Power Engineering, 2021, Vol. 42, Issue 4, Pages: 144-150* 42(4): 144–50. http://hdlgc.xml-journal.net/en/article/doi/10.13832/j.jnpe.2021.04.0144 (June 8, 2022).

Liu, Peng, and Jinting Liu. 2020. ‘Combined Effect of Multiple Performance Shaping Factors on Human Reliability: Multiplicative or Additive?’*International Journal of Human–Computer Interaction* 36(9): 828–38. https://www.tandfonline.com/doi/abs/10.1080/10447318.2019.1695461 (June 8, 2022).

Matías, J. M., T. Rivas, J. E. Martín, and J. Taboada. 2008. ‘A Machine Learning Methodology for the Analysis of Workplace Accidents.’*International Journal of Computer Mathematics* 85(3–4): 559–78.

Matthew Alders, Anne Marie Rafferty, and Janet E. Anderson. 2022. *Using the Resilience Assessment Grid to Analyse and Improve Organisational Resilience of a Hospital Ward*. Eds. Christopher P. Nemeth and Erik Hollnagel. Switzerland: Springer.

McCafferty, Denise B. 1995. ‘Successful System Design through Integrating Engineering and Human Factors.’*Process Safety Progress* 14(2): 147–51. https://onlinelibrary.wiley.com/doi/full/10.1002/prs.680140209 (June 8, 2022).

Mkrtchyan, L., L. Podofillini, and V. N. Dang. 2014. ‘A Survey of Bayesian Belief Network Applications in Human Reliability Analysis.’*Safety and Reliability:*

Methodology and Applications – Proceedings of the European Safety and Reliability Conference, ESREL 2014: 1073–81.

Mkrtchyan, L., L. Podofillini, and V.N. Dang. 2015. 'Bayesian Belief Networks for Human Reliability Analysis: A Review of Applications and Gaps.'*Reliability Engineering & System Safety* 139: 1–5. http://www.sciencedirect.com/science/article/pii/S0951832015000514.

Mood, Alexander, Franklin A. Graybill, and Duane C. Boes. 1974. *Introduction to the Theory of Statistics*. Kinsport Press, Inc.

Morais, Caroline et al. 2022. 'Identification of Human Errors and Influencing Factors: A Machine Learning Approach.'*Safety Science* 146.

Moura R et al. 2014. 'Human Error Analysis: Review of Past Accidents and Implications for Improving Robustness of System Design.'*Safety and Reliability: Methodology and Applications*: 1037–46. http://www.crcnetbase.com/doi/abs/10.1201/b17399-147.

Moura Raphael, Michael Beer, Edoardo Patelli, and John Lewis. 2017. 'Learning from Major Accidents: Graphical Representation and Analysis of Multi-Attribute Events to Enhance Risk Communication.'*Safety Science* 99: 58–70.

Murchison, Nicole, and Walter Edgar Gilmore. 2018. *Human Reliability Analysis (HRA): Comparison of Methods. (Conference) | OSTI.GOV*. https://www.osti.gov/biblio/1515627 (June 8, 2022).

Nagarajan, Radhakrishnan, Marco Scutari, and Sophie Lèbre. 2013. 'Bayesian Network Inference Algorithms.'In *Bayesian Networks in R*, New York: Springer, 85–101. https://link.springer.com/chapter/10.1007/978-1-4614-6446-4_4 (June 15, 2022).

National Bureau of Statistics. 2022. *中华人民共和国2021年国民经济和社会发展统计公报*. http://www.stats.gov.cn/tjsj/zxfb/202202/t20220227_1827960.html (June 22, 2022).

National Mine Safety Administration of China. 2022. '2021年全国矿山安全生产事故情况.'https://www.chinamine-safety.gov.cn/zfxxgk/fdzdgknr/sgcc/202202/t20220223_408504.shtml (June 22, 2022).

National Safety Council of US. 2021. 'Industry Profiles – Injury Facts.'https://injuryfacts.nsc.org/work/industry-incidence-rates/industry-profiles/ (June 8, 2022).

Neapolitan, Richard E. 2004. *Learning Bayesian Networks*. Pearson.

Nguyen, Loc. 2018. 'Specifying Prior Probabilities in Bayesian Network by Maximum Likelihood Estimation Method.'*Sylwan Journal* 160(2): 281–98. https://www.researchgate.net/publication/298392948.

Nicola Laver LLB. 2020. 'Machinery Accident Claims.'https://www.claims.co.uk/accidents-at-work/machinery-accident-claims (June 8, 2022).

NIST/SEMATECH. 2012. 'Critical Values of the Chi-Square Distribution.'In *E-Handbook of Statistical Methods*, https://www.itl.nist.gov/div898/handbook/eda/section3/eda3674.htm (June 15, 2022).

Norazahar, Norafneeza Binti. 2020. 'Human Factors Risk Assessment.'In *Methods in Chemical Process Safety*, Elsevier, 289–302.

Pan, Xing, and Zekun Wu. 2020. 'Performance Shaping Factors in the Human Error Probability Modification of Human Reliability Analysis.'*International journal of occupational safety and ergonomics: JOSE* 26(3): 538–50. https://pubmed.ncbi.nlm.nih.gov/30295571/ (June 8, 2022).

Pasquale, Valentina di, Raffaele Iannone, Salvatore Miranda, and Stefano Riemma. 2013. 'An Overview of Human Reliability Analysis Techniques in Manufacturing Operations.'*Operations Management*. Undefined/state.item.id (June 24, 2022).

'Probability and Statistics Symbols.'*Math Vault*. https://mathvault.ca/hub/higher-math/math-symbols/probability-statistics-symbols/ (September 11, 2020).

Rasoul Jamshidi, and Mohammad Ebrahim Sadeghi. 2021. 'Neural Network Based Human Reliability Analysis Method in Production Systems.'*Journal of Applied Research on Industrial Engineering* 8(3): 236–50. https://www.researchgate.net/publication/355479332_Neural_network_based_human_reliability_analysis_method_in_production_systems (June 8, 2022).

Santiasih, I, and R A Ratriwardhani. 2021. 'Human Error Probability Analysis Using Success Likelihood Index Method (SLIM) Approach in Grinding Activities.'*IOP Conference Series: Materials Science and Engineering* 1072: 012–027. https://iopscience.iop.org/article/10.1088/1757-899X/1072/1/012027 (June 8, 2022).

Sehsah, Radwa, Abdel Hady El-Gilany, and Ateya Megahed Ibrahim. 2020. ‘Personal Protective Equipment (PPE) Use and Its Relation to Accidents among Construction Workers.’*work, environment and health* 111(4): 285. /pmc/articles/PMC7809954/ (July 16, 2022).

Sharma, Garima, and Rajiv Nandan Rai. 2021. ‘Methodology to Select Human Reliability Analysis Technique for Repairable Systems.’*Safety and Reliability Modeling and Its Applications*: 261–83.

Da Silva, Polyana Almeida, Marcelo Albuquerque de Oliveira, Gabriela de Mattos Veroneze, and Camila Maria Costa da Silva. 2021. ‘Management Proposal for Consumable Item Control in an Electronic Company Using Concept of Human Reliability and Quality Tools.’*European Journal of Engineering and Technology Research* 6(6): 145–53.

Slim, Hussein, and Sylvie Nadeau. 2020. ‘A Proposition for Combining Rough Sets, Fuzzy Logic and FRAM to Address Methodological Challenges in Safety Management: A Discussion Paper.’*Safety* 6(4): 50. https://www.mdpi.com/2313-576X/6/4/50/htm (June 8, 2022).

Spirtes, Peter, and Richard Scheines. 1993. The MIT Press *Causation, Prediction, and Search*.

Steck, Harald. 2008. ‘Learning the Bayesian Network Structure: Dirichlet Prior versus Data.’In *Proceedings of the 24th Conference on Uncertainty in Artificial Intelligence (UAI2008)*, 511–18. https://arxiv.org/abs/1206.3287v1 (June 20, 2022).

Stretton, Paul. 2020. ‘The Lilypond: An Integrated Model of Safety II Principles in the Workplace. A Quantum Shift in Patient Safety Thinking:’*Journal of Patient Safety and Risk Management* 25(2): 85–90. https://journals.sagepub.com/doi/abs/10.1177/2516043520913420 (June 8, 2022).

Stuart, A., and K. Ord. 1994. §8.7 *Kendall's Advanced Theory of Statistics: Volume I—Distribution Theory, 6th Edition*. John Wiley & Sons. Advanced+Theory+of+Statistics%2C+Volume+1%2C+Distribution+Theory%2C+6th+Edition-p-9780470665305 (June 13, 2022).

Swain, A D, and H E Guttmann. 1983. *Handbook of Human-Reliability Analysis with Emphasis on Nuclear Power Plant Applications. Final Report*. Albuquerque, NM, and Livermore, CA (United States). http://www.osti.gov/servlets/purl/5752058/ (June 8, 2022).

Verma, Thomas S. 1995. 'A THEORY OF INFERRED CAUSATION.' *Studies in Logic and the Foundations of Mathematics* 134(1): 789–811.

Vladykina, Svetlana, and Thomas Wolfgang Thurner. 2019. 'Cognitive Reliability Error Analysis Method (CREAM) at the International Thermonuclear Experimental Reactor (ITER).' *Quality and Reliability Engineering International* 35(6): 1621–33. https://onlinelibrary.wiley.com/doi/full/10.1002/qre.2464 (June 8, 2022).

Wang, Jianhao, and Mingwei Yan. 2019. 'Application of an Improved Model for Accident Analysis: A Case Study.' *International Journal of Environmental Research and Public Health* 16(15).

Wang, Zhiru et al. 2015. 'Human Error Risk Management Methodology for Rail Crack Incidents.' *Urban Rail Transit* 1(4): 257–65.

Wasserman, Larry. 2004. *All of Statistics : A Concise Course in Statistical Inference*. Springer.

Woolley, Matthew James, Natassia Goode, Gemma J.M. Read, and Paul M. Salmon. 2019. 'Have We Reached the Organisational Ceiling? A Review of Applied Accident Causation Models, Methods and Contributing Factors in Construction.' *Theoretical Issues in Ergonomics Science* 20(5): 533–55. https://www.tandfonline.com/doi/abs/10.1080/1463922X.2018.1558305 (June 8, 2022).

Work Safety Commission of the State Council. 2018. *国务院安委会办公室关于2018年上半年全国建筑业安全生产形势的通报.* https://www.mem.gov.cn/gk/tzgg/tb/201807/t20180725_230568.shtml (June 22, 2022).

Yan, Dawen, Guotai Chi, and Kin Keung Lai. 2020. 'Financial Distress Prediction and Feature Selection in Multiple Periods by Lassoing Unconstrained Distributed Lag Non-Linear Models.' *Mathematics* 8(8): 1275. https://www.mdpi.com/2227-7390/8/8/1275/htm (June 8, 2022).

Yi Tang, and Sargur N. Srihari. 2012. 'Efficient and Accurate Learning of Bayesian Networks Using Chi-square Independence Tests | IEEE Conference Publication | IEEE Xplore.' *21st International Conference on Pattern Recognition (ICPR 2012)*. https://ieeexplore.ieee.org/document/6460728 (June 15, 2022).

Zhang, Ling, Yu Jie Zhu, Lin Xiu Hou, and Hu Chen Liu. 2021. 'New Method for Dependence Assessment in Human Reliability Analysis Based on Linguistic

Hesitant Fuzzy Information.'*Nuclear Engineering and Technology* 53(11): 3675–84.

Zhu, Rongchen, Xiaofeng Hu, Jiaqi Hou, and Xin Li. 2021. 'Application of Machine Learning Techniques for Predicting the Consequences of Construction Accidents in China.'*Process Safety and Environmental Protection* 145: 293–302.

Zwillinger, Daniel. Kokoska. 2019. *CRC Standard Probability and Statistics Tables and Formular*. CRC PRESS.

Appendix A. Assessment Model for Gas Turbine Failure

Part I. Dependency Tables of the Assessment Model for Gas Turbine Failure

Assumptions for the dependency tables:

1) Trace failures only for the "**operation mode**". Failures related to design, manufacturing, and assembly are not considered here. The same for "foreign objects" and "unexpected causes".

2) Relations are catalogued in "direct" and "indirect". For the indirect case, the chain of contributors needs to be described.

Split B6, B10:

1) Consider two different types of overheating (B6), which are thermal overheating (B6T) and mechanical overheating (B6M). *B6T means that overheating is caused by thermal reasons, while B6M means that overheating is caused by mechanical reasons.*

2) Consider two different types of vibration (B10), which are thermal vibration (B10T) and mechanical vibration (B10M). *The former represents the vibration caused by thermos-acoustics, while the latter represents the vibration for other mechanical reasons.*

Table A-13. Dependency table from Group C to Group D

Contribution from C to D (Core Components C & Main Components D)	
Contributor I	**Consequence (D)**
Compressor Blading (C1)	Rotor(D1)
	Compressor(D2)
	Combustion Chamber(D3)
	Turbine(D4)
Combustor (C2)	Combustion Chamber(D3)
	Turbine(D4)
Turbine Blading (C3)	Rotor(D1)
	Turbine(D4)
Bearing (C4)	Rotor(D1)
	Compressor(D2)
	Turbine(D4)

All the dependencies in the above table are direct.

Table A-14. Dependency table from Group B to Group C

Contributor（B）	**Consequence (C)**	**Type of relation**	**Relation chain**
Overspeed (B1)	Compressor Blading (C1)	direct	B1>C1
	Combustor (C2)	direct	B1>C2
	Turbine Blading (C3)	direct	B1>C3
	Bearing (C4)	direct	B1>C4
Sealing Rupture (B2)	Compressor Blading (C1)	indirect	B2>B6M>C1
	Turbine Blading (C3)	indirect	B2>B6M>C3
Blading Rupture (B3)	Compressor Blading (C1)	indirect	B3>B6M>C1 B3>B10M>C1
	Turbine Blading (C3)	indirect	B3>B6M>C3 B3>B10M>C3
TBC Spallation (B4)	Combustor (C2)	direct	B4>C2
	Turbine Blading (C3)	direct	B4>C3
Misalignment (B5)	Compressor Blading (C1)	indirect	B5>B2>B6M>C1 B5>B3>B6M>C1
	Turbine Blading (C3)	indirect	B5>B2>B6M>C3 B5>B3>B6M>C3
Overheating (B6T)	Combustor (C2)	indirect	B6T>B4>C2
	Turbine Blading (C3)	indirect	B6T>B4>C3
Overheating (B6M)	Compressor Blading (C1)	direct	B6M>C1
	Turbine Blading (C3)	direct	B6M>C3
Vibration (B10T)	Combustion (C2)	direct	B10T>C2
Vibration (B10M)	Compressor Blading (C1)	direct	B10M>C1
	Turbine Blading (C3)	direct	B10M>C3

Table A-15. Dependency table from Group A to Group C

Contributor(A)	**Consequence (C)**	**Type of relation**	**Relation chain**
Fuel System (A1)	Compressor Blading (C1)	indirect	A1>B1>C1
	Combustor (C2)	indirect	A1>B1>C2 A1>B6T>B4>C2
	Turbine Blading (C3)	indirect	A1>B1>C3 A1>B6T>B4>C3
	Bearing (C4)	indirect	A1>B1>C4
Lube Oil System (A2)	Compressor Blading (C1)	indirect	A2>C4>C1
	Turbine Blading (C3)	indirect	A2>C4>C3
	Bearing (C4)	direct	A2>C4
Hydraulic/Pneumatic Control System (A3)	Combustor (C2)	indirect	A3>A1>B6T> B4>C2
	Turbine Blading (C3)	indirect	A3>A1>B6T>B4>C3
Digital Control System (A4)	Compressor Blading (C1)	indirect	A4>A3>A1>B1>C1
	Combustor (C2)	indirect	A4>A3>A1>B6T>B4>C2
	Turbine Blading (C3)	indirect	A4>A3>A1>B1>C3 A4>A3>A1>B6T>B4>C3
	Bearing (C4)	indirect	A4>B1>C4 A4>C6>A2>C4
	auxiliary Pump (C6)	direct	A4>C6
Secondary AirCooling System (A5)	Combustor (C2)	indirect	A5>B6T>B4>C2
	Turbine Blading (C3)	indirect	A5>B6T>B4>C3
Uninterruptible Power Supply (UPS) (A6)	Compressor blading (C1)	Indirect	A6>C6>A2>C4>C1
	Turbine blading (C3)	indirect	A6>C6>A2>C4>C3

Table A-16. Dependency table from Group C to Group A

Contributor (C)	Consequence (A)	Type of relation	Relation chain
AC pump (C5)	Lube Oil System (A2)	direct	C5>A2
DC pump (C6)		direct	C6>A2

Table A-17. Dependency table from Group A to Group B

Contributor (A)	Consequence (B)	Type of relation	Relation chain
Fuel System (A1)	Overspeed (B1)	direct	A1>B1
	TBC Spallation (B4)	indirect	A1>B6T>B4
	Overheating (B6T)	direct	A1>B6T
	Vibration (B10T)	direct	A1>B10T
Lube Oil System (A2)			
Hydraulic/Pneumatic Control System (A3)	Overspeed (B1)	indirect	A3>A1>B1
	Misalignment (B5)	indirect	A3>A1>B6T>B5
	Overheating (B6)	indirect	A3>A1>B6T
Digital Control System (A4)	Overspeed (B1)	indirect	A4>A3>A1>B1
	Sealing Rupture (B2)	indirect	A4>A3>A1>B6T>B2
	Blading Rupture (B3)	indirect	A4>A3>A1>B6T>B3
	Misalignment (B5)	indirect	A4>A3>A1>B6T>B5
	Overheating (B6T)	indirect	A4>A3>A1>B6T
Secondary Air Cooling System (A5)	Sealing Rupture (B2)	indirect	A5>B6T>B2
	Blading Rupture (B3)	indirect	A5>B6T>B3
	TBC Spallation (B4)	indirect	A5>B6T>B4
	Overheating (B6T)	direct	A5>B6T
Uninterruptible Power Supply (UPS) (A6)	n/a		

Table A-18. Dependency table within Group A

Contributor(A)	Consequence (A)	Type of relation
Fuel System (A1)	n/a	
Lue Oil System(A2)	n/a	
Hydraulic/Pneumatic Control System (A3)	Fuel System (A1)	direct
Digital Control System (A4)	Hydraulic/Pneumatic Control System (A3)	direct
Secondary Air Cooling System (A5)	n/a	
Uninterruptible Power Supply (UPS) (A6)	n/a	

Table A-19. Dependency table within Group B

Contributor (B)	Consequence (B)	Type of relation
Overspeed (B1)	Sealing Rupture (B2)	direct
	Blade Rupture (B3)	direct
	Overheating (B10M)	direct
Sealing Rupture (B2)	Overheating (B6M)	direct
Blade Rupture (B3)	Overheating (B6M)	direct
	Vibration (B10M)	direct
TBC Spallation (B4)		
Misalignment (B5)	Sealing Rupture (B2)	direct
	Blade Rupture (B3)	direct
	Overheating (B6M)	direct
Overheating (B6T)	Sealing Rupture (B2)	direct
	Blading Rupture (B3)	direct
	TBC Spallation (B4)	direct
	Misalignment (B5)	direct
Overheating (B6M)	n/a	
Vibration (B10T)	n/a	
Vibration (B10M)	n/a	

Table A-20. Dependency table within Group C

Contributor (C)	Consequence (C)	Type of relation
Compressor Blading (C1)	n/a	
Combustor (C2)	C3	direct
Turbine Blade (C3)	n/a	
Bearing (C4)	Compressor Blading (C1)	direct
	Turbine Blading (C3)	direct
AC Pump (C5)	n/a	
Emergency pump (C6)	n/a	

Backup system:

Consider UPS as a backup to initiate the emergency pump. The way to deal with the backup system is to build the relation chain following *'Protection control→*

acts on→ to supply→ safeguards' and 'backup system→ acts on→ to supply→ safeguards'.

Table A-21. Dependency table referring to the backup system

Protection control	**backup system** (not permanently)	acts on (not permanently)	to supply	safeguards
DCS (A4)	Uninterruptible Power Supply (UPS) (A6)	Emergency pump (C6)	Lube oil system (A2)	Bearing (C4) >
				>Sealing rupture (B2) >Blading rupture (B3) >Misalignment (B5) >Overheating B6M) >Compres. Blading (C1) >Turbine blading (C3)

The relation chain adapted from the above table:

A4>C6>A2>C4>B2

A6>C6>A2>C4>B3

A4>C6>A2>C4>B5

A6>C6>A2>C4>B6M

and

A4>C6>A2>C4>C1

A6>C6>A2>C4>C3

Emergency protection system:

Emergency protection systems do not cause damage when not in operation. These systems must operate only in emergency cases and not permanently. A fail-safe system will generally control the emergency protection systems. In any case, such a system will start acting when a specific limit value is exceeded. The emergency protection systems considered here are:

- Thermo acoustic induced vibration (B10T)
- Mechanical vibration (B10M)
- Overspeed (B1)

The way to deal with the protection system is to build the relation chain following '*Protection control→ Protection system→ Safeguard's and 'Protection control→ acts on→ Secures/assist→ safeguards'*. The former chain only acts in an emergency, while the latter operates in regular situations.

Table A-22. Dependency table referring to the protection system B10T

Protection control	**Protection system**	acts on	Secures / assists	safeguards
DCS (A4)	Anti-humming Vibration (B10T)	Hydraulic/Pneumatic Control System (A3)	Fuel system (A1)	Combustor (C2)

The relation chain adapted from the above table:

A4 > B10T > C2

A4 > A3 > A1 > … > C2

the relation from A1 to C2 is indirect, which can be found in the table of the relation between groups A&C

Table A-23. Dependency table referring to protection system B10M

Protection control	**Protection system**	Acts on	Secures /assists	Safeguards
DCS (A4)	Vibration (B10M)	Hydraulic / Pneumatic Control System (A3)	Fuel system (A1)	Compressor blading (C1) Turbine blading (C3)

The relation chain adapted from the above table:

A4>B10M>C1;

A4>B10M>C3;

A4>A3>A1>…>C1

A4>A3>A1>…>C3

The relations from A1 to C1, and C3 are indirect, which can be found in the table of the relationship between groups A&C

Table A-24. Dependency table referring to protection system B1

Protection control	Protection system	Acts on (not permanently)	Secures / assists	Safeguards
DCS (A4)	Over-speed (B1)	Hydraulic/Pneumatic Control System (A3)	Fuel system (A1)	Compressor blading (C1) Combustor (C2) Turbine blading (C3) Bearing (C4)

The relation chain adapted from the above table:

A4 > B1 > C1;

A4 > B1 > C2;

A4 > B1 > C3;

A4 > B1 > C4;

A4 > A3 > A1 > … > C1

A4 > A3 > A1 > … > C3

A4 > A3 > A1 > … > C1

A4 > A3 > A1 > … > C3

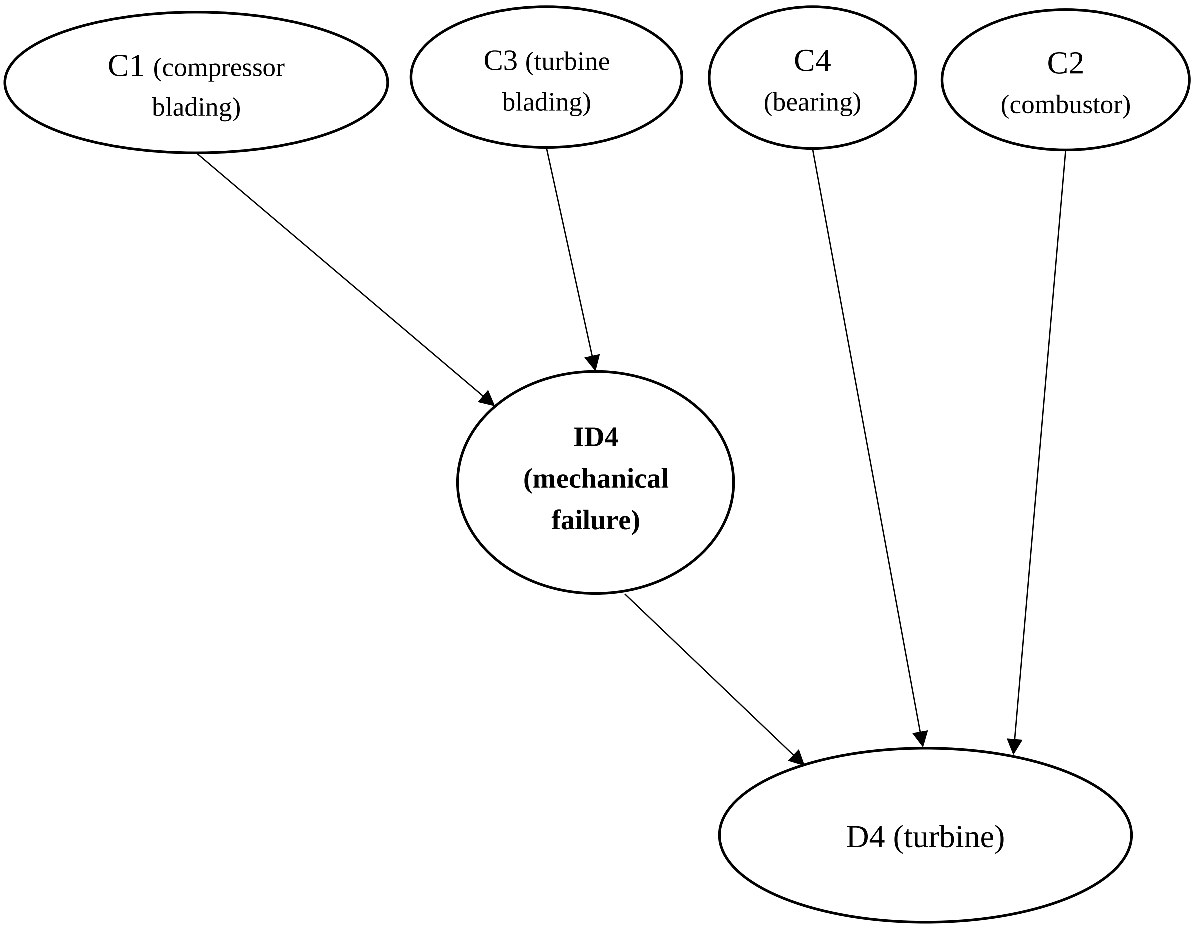
The relations from A1 to C1, C2, C3, and C4 are indirect, which can be found in the table of the relation between groups A & C

Part II. Intermedia Nodes for the Assessment Model for Gas Turbine Failure

Six nodes (B2, B3, B6M, C1, C3, and D4) with more than three parents were dealt with by introducing intermedia nodes to reduce the size of the conditional probability table.

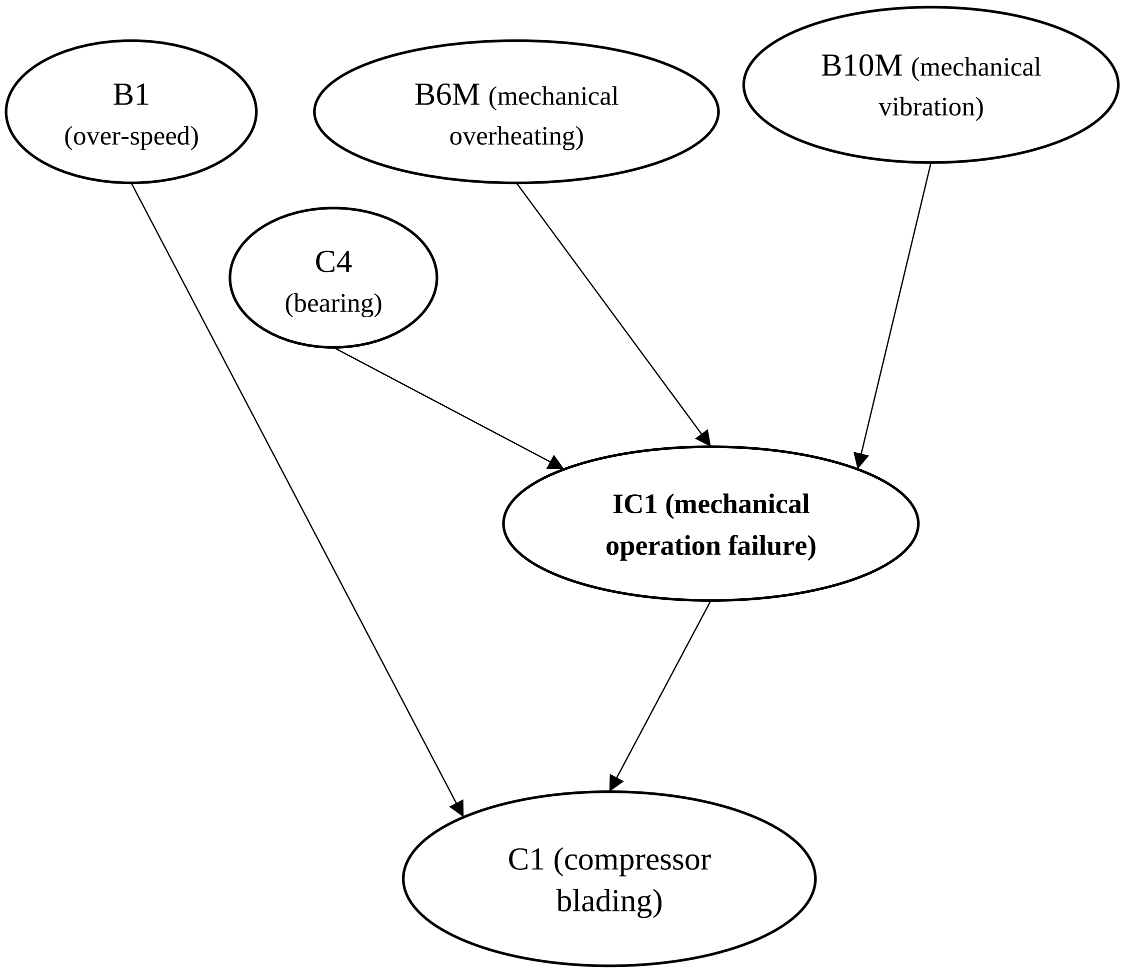
(i). Intermedia nodes of D4

<table>
<tr><td>Initial parents of D4</td><td>C1
(compressor blading)</td><td>C3
(turbine blading)</td><td rowspan="2">C4
(bearing)</td><td rowspan="2">C2
(combustor)</td></tr>
<tr><td>Parents of D4 with intermedia nodes</td><td colspan="2">ID4 (Mechanical failure)</td></tr>
</table>



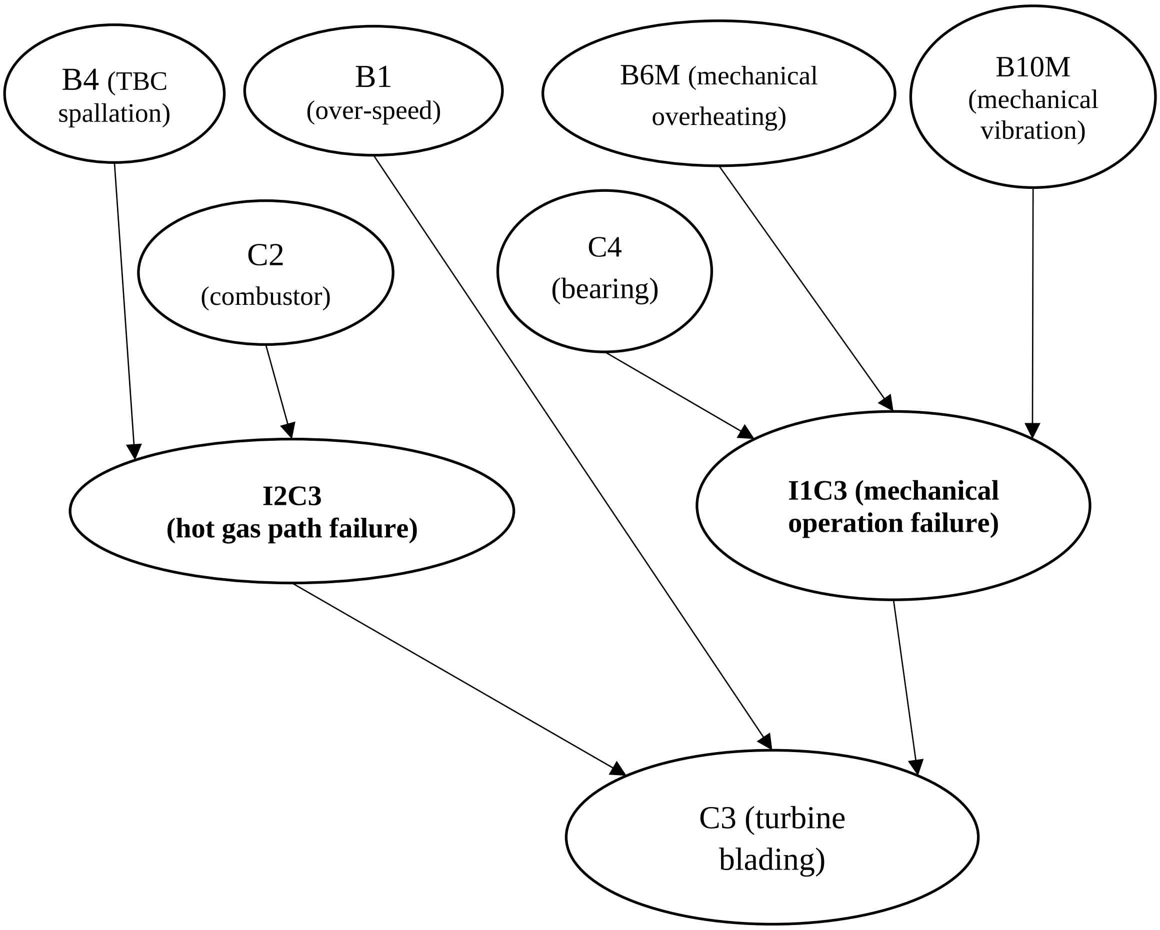
(ii). Intermedia nodes of C1

<table>
<tr><td>Initial parents of C1 (compressor blading)</td><td>C4 (bearing)</td><td>B6M (mechanical overheating)</td><td>B10M (mechanical vibration)</td><td rowspan="2">B1 (overspeed)</td></tr>
<tr><td>Parents of C1 with intermedia nodes</td><td colspan="3">IC1 (mechanical operation failure)</td></tr>
</table>



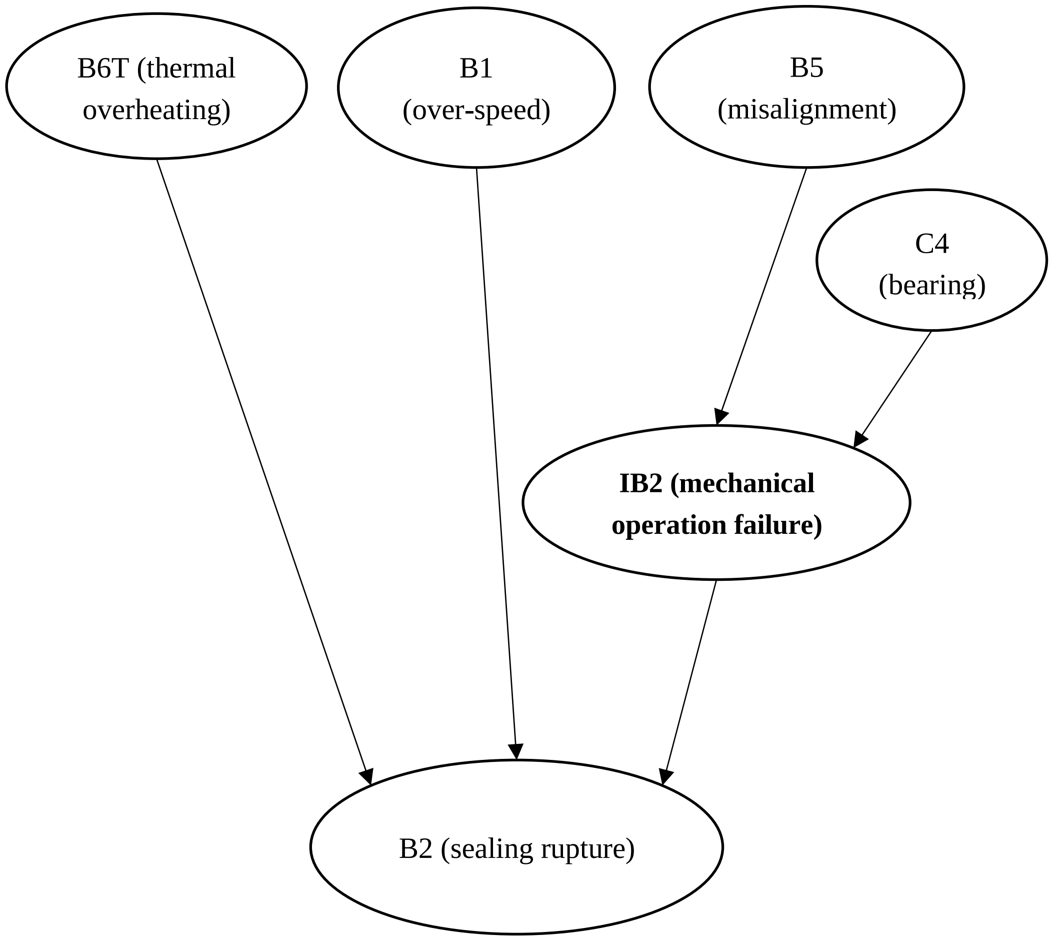
(iii). Intermedia nodes of C3

<table>
<tr><td>Initial parents of C3 (turbine blading)</td><td>B6M (mechanical overheating)</td><td>B10M (mechanical vibration)</td><td>C4 (bearing)</td><td rowspan="2">B1 (oversp eed)</td><td>B4 (TBC spallation)</td><td>C2 (combusto r)</td></tr>
<tr><td>Parents of C3 with intermedia nodes</td><td colspan="3">I1C3
(mechanical operation failure)</td><td colspan="2">I2C3
(hot gas path failure)</td></tr>
</table>



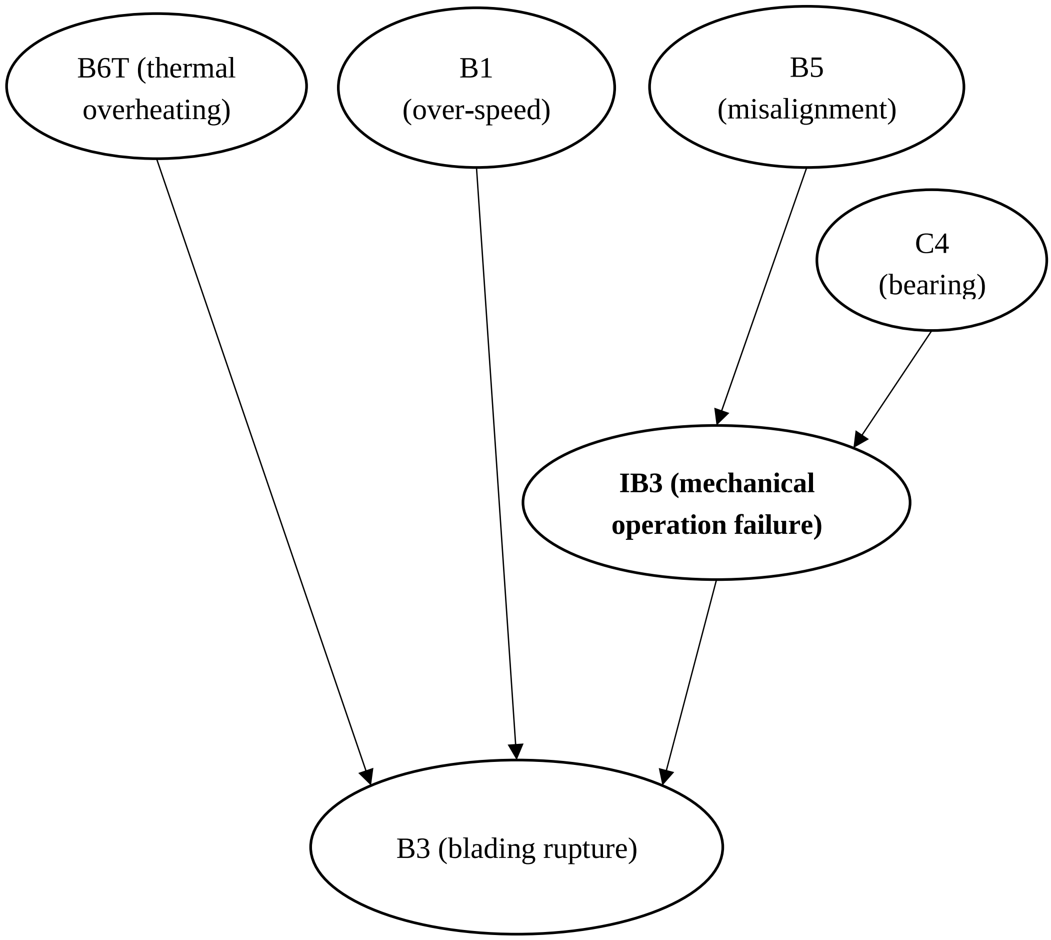
(iv). Intermedia nodes of B2

<table>
<tr><td>Initial parents of B2 (sealing rupture)</td><td>C4 (bearing)</td><td>B5 (misalignment)</td><td rowspan="2">B1 (overspeed)</td><td rowspan="2">B6T (thermal overheating)</td></tr>
<tr><td>Parents of B2 with intermedia nodes</td><td colspan="2">IB2 (mechanical operation failure)</td></tr>
</table>



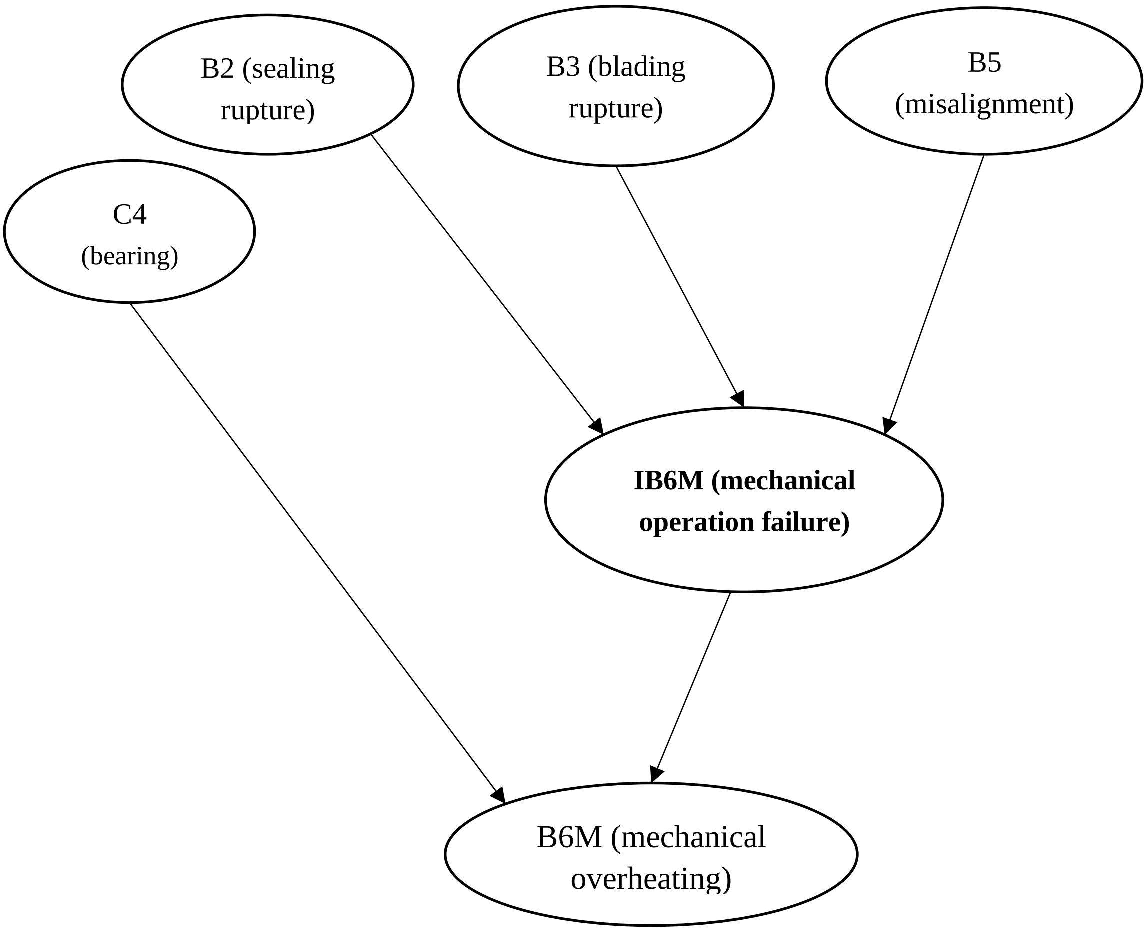
(v). Intermedia nodes of B3

<table>
<tr><td>Initial parents of B3 (blading rupture)</td><td>C4 (bearing)</td><td>B5 (misalignment)</td><td rowspan="2">B1 (overspeed)</td><td rowspan="2">B6T (thermal overheating)</td></tr>
<tr><td>Parents of B3 with intermedia nodes</td><td colspan="2">IB3 (mechanical operation failure)</td></tr>
</table>



(vi). Intermedia nodes of B6M

<table>
<tr><td>Initial parents of B6M (mechanical overheating)</td><td>B2 (sealing rupture)</td><td>B3 (blading rupture)</td><td>B5 (misalignment)</td><td rowspan="2">C4 (bearing)</td></tr>
<tr><td>Parents of B6M with intermedia nodes</td><td colspan="3">IB6M (mechanical operation failure)</td></tr>
</table>



Part III. Dependency Tables of the Assessment Model for Gas Turbine Failure

The symbol 'R' represents 'Regularly', which means the component/function is working regularly or normal, and no problem existed (no over-speed, no overheating, no misalignment, no vibration, no spallation, or no rupture).

The symbol 'I' represents 'Irregularly,' which means the component/function is working irregularly or abnormally, or some problem exists, like over-speed, overheating, misalignment, vibration, spallation, or rupture.

For example,

- A1(fuel system) =' R' means that the fuel system is in good condition without any problem.
- A1(fuel system) =' I' means something is wrong with the fuel system.
- B1(over-speed) =' R' means that the working condition is fine without over-speed.
- B1(over-speed) =' I' means that there is a failure, specifically an over-speed problem.

(i). Probability table of group A

Conditional Probability Table of A1

The condition of A3 (hydraulic/ pneumatic control system)	Probability of A1 (fuel system)		
	A1=I	A1=R	
I	0.8	0.2	
R	0.01	0.99	Operation fault, faulty maintenance

Probability table of A2

C5 (AC pump)	C6 (emergency pump)	Probability of A2 (lube oil system)	
		A2= I	A2=R
I	I	1	0
R	I	0	1
I	R	0	1
R	R	0	1

Conditional Probability Table of A3

Condition of A4 (digital control system)	Probability of A3 (hydraulic/ pneumatic control system)		
	A3= I	A3=R	
I	0.9	0.1	
R	0.001	0.999	false information by DCS

Probability table of A4

Probability of A4 (digital control system)	
A4= I	A4=R
0.001	0.999

Probability table of A5

Probability of A5 (secondary air cooling system)		
A5= I	A5=R	blocking of cooling holes, operation in the wrong environment
0.001	0.999	

Conditional Probability Table of A6

Probability of A6 (UPS)	
A6= I	A6=R
0.001	0.999

(ii). Probability table of group B

B1 (overspeed)

Conditional Probability Table of B1

A1 (fuel system)	A4 (digital control system)	Probability of B1 (overspeed)	
		B1=I	B1=R
I	I	0.99	0.01
R	I	0.9	0.1
I	R	0.2	0.8
R	R	0.001	0.999

B2 (sealing rupture)

The original conditional probability table of B2

B1 (overspeed)	B5 (misalignment)	B6T (overheating)	C4 (bearing)	Probability of B2 (sealing rupture)	
				B2=I	B2=R

Introduced the intermedia nodes, then

Conditional probability table of B2

B1 (overspeed)	B6T (thermal overheating)	IB2 (Mechanical operation failure)	Probability of B2 (sealing rupture)	
			B2=I	B2=R
I	I	I	1.0	0.0
R	I	I	0.7	0.3
I	R	I	1	0
R	R	I	0.3	0.7
I	I	R	1	0
R	I	R	0.6	0.4
I	R	R	1	0
R	R	R	0.001	0.999

conditional probability table of IB2

B5 (misalignment)	C4 (bearing)	Probability of IB2 (Mechanical operation failure)	
		IB2=I	IB2=R
I	I	1	0
R	I	0.6	0.4
I	R	0.8	0.2
R	R	0	1

B3 (blading rupture)

The original conditional probability table of B3

B1 (overspeed)	B5 (misalignment)	B6T (thermal overheating)	C4 (bearing)	Probability of B3 (blading rupture)	
				B3=I	B3=R

Introduced the intermedia nodes, then

conditional probability table of B3

B1 (overspeed)	B6T (thermal overheating)	IB3 (Mechanical operation failure)	Probability of B3 (blading rupture)	
			B3=I	B3=R
I	I	I	1.0	0.0
R	I	I	0.7	0.3
I	R	I	1	0
R	R	I	0.3	0.7
I	I	R	1	0
R	I	R	0.6	0.4
I	R	R	1	0
R	R	R	0.001	0.999

conditional probability table of IB3

B5 (misalignment)	C4 (bearing)	Probability of IB3 (Mechanical operation failure)	
		IB3=I	IB3=R
I	I	1	0
R	I	0.6	0.4
I	R	0.8	0.2
R	R	0	1

B4 (TBC spallation)

Conditional Probability Table of B4

The Condition of B6T (thermal overheating)	Probability of B4 (TBC spallation)		
	B4=I	B4=R	
I	0.9	0.1	
R	0.001	0.999	damage by foreign objects

B5 (misalignment)

Conditional Probability Table of B5

A4 (digital control system)	B6T (thermal overheating)	C4	Probability of B5(misalignment)		
			B5=I	B5=R	
I	I	I	0.8	0.2	
R	I	I	0.7	0.3	
I	R	I	0.6	0.4	
R	R	I	0.1	0.9	
I	I	R	0.7	0.3	
R	I	R	0.6	0.4	
I	R	R	0.1	0.9	
R	R	R	0.01	0.99	Human error (assembly phase)

B6T (thermal overheating)

Conditional Probability Table of B6T

A1 (fuel system)	A5 (secondary air cooling system)	Probability of B6T (thermal overheating)	
		B6T=I	B6T=R
I	I	1	0
R	I	0.9	0.1
I	R	0.9	0.1
R	R	0.001	0.999

B6M (mechanical overheating)

The original conditional probability table of B6M

B2 (sealing rupture)	B3 (blading rupture)	B5 (misalignment)	C4 (bearing)	Probability of B6M (mechanical overheating)	
				B6M=I	B6M=R

Introduced intermedia nodes. Then

conditional probability table of B6M

C4 (bearing)	IB6M (mechanical operation failure)	Probability of B6M (mechanical overheating)	
		B6M=I	B6M=R
I	I	0.9	0.1
R	I	0.8	0.2
I	R	0.6	0.4
R	R	0.001	0.999

Conditional Probability Table of IB6M

B2 (sealing rupture)	B3 (blading rupture)	B5 (misalignment)	Probability of IB6M (mechanical operation failure)	
			IB6M=I	IB6M=R
I	I	I	1	0
R	I	I	0.9	0.1
I	R	I	0.7	0.3
R	R	I	0.5	0.5
I	I	R	0.9	0.1
R	I	R	0.8	0.2
I	R	R	0.5	0.5
R	R	R	0	1

B10T (thermos acoustic-induced vibration

Conditional Probability Table of B10T

A1 (fuel system)	A4 (digital control system)	Probability of B10T (138hermos acoustic induced vibration)	
		B10T=I	B10T=R
I	I	0.9	0.1
R	I	0.8	0.2
I	R	0.4	0.6
R	R	0.001	0.999

B10M (vibration)

Conditional Probability Table of B10M

A4 (digital control system)	B1 (overspeed)	B3 (blading rupture)	Probability of B10M (vibration)		
			B10M=I	B10M=R	
I	I	I	1.0	0	
R	I	I	0.05	0.95	
I	R	I	0.3	0.7	
R	R	I	0.3	0.7	
I	I	R	1	0	
R	I	R	0.05	0.95	
I	R	R	0.01	0.99	
R	R	R	0.001	0.999	degradation of the blading material

If DS is good, it can control and limit the effect of overspeed and rupture.

(iii). Probability table of Group C

C1 (compressor blading)

The original conditional probability table of C1

B1 (overspeed)	B6M (mechanical overheating)	B10M (vibration)	C4 (bearing)	Probability of C1 (compressor blading)	
				C1=I	C1=R

Introduced the intermedia nodes, then

conditional probability table of C1

B1 (over speed)	IC1 (Mechanical operation failure)	Probability of C1 (compressor blading)	
		C1=I	C1=R
I	I	1	0
R	I	0.9	0.1
I	R	1	0
R	R	0.001	0.999

conditional probability table of IC1

B6M (mechanical overheating)	B10M (vibration)	C4 (bearing)	Probability of IC1 (Mechanical operation failure)	
			IC1=I	IC1=R
I	I	I	1	0
R	I	I	0.8	0.2
I	R	I	0.7	0.3
R	R	I	0.2	0.8
I	I	R	0.9	0.1
R	I	R	0.8	0.2
I	R	R	0.7	0.3
R	R	R	0	1

C2 (combustor)

Conditional probability table of C2

B1 (over speed)	B4 (TBC spallation)	B10T (thermos acoustic induced vibration)	Probability of C2 (combustor)		
			C2=I	C2=R	
I	I	I	1.0	0.0	
R	I	I	0.8	0.2	
I	R	I	1	0	
R	R	I	0.7	0.3	
I	I	R	1	0	
R	I	R	0.6	0.4	
I	R	R	1	0	
R	R	R	0.001	0.999	degradation effect

C3 (turbine blading)

The original conditional probability table of C3

B1 (over-speed)	B4 (TBC spallation)	B6M (mechanical overheating)	B10M (vibration)	C2 (combustor)	C4 (bearing)	Probability of C3(turbine blading)	
						C3=I	C3=R

Introduced intermedia nodes. Then

Conditional probability table of C3

B1 (over speed)	I1C3 (Mechanical operation failure)	I2C3 (hot gas path failure)	Probability of C3 (turbine blading)	
			C3=I	C3=R
I	I	I	1.0	0.0
R	I	I	0.98	0.02
I	R	I	1	0
R	R	I	0.8	0.2
I	I	R	1	0
R	I	R	0.9	0.1
I	R	R	1	0
R	R	R	0.001	0.999

Conditional probability table of I1C3

B6M (mechanical overheating)	B10M (vibration)	C4 (bearing)	Probability of I1C3 (Mechanical operation failure)	
			I1C3=I	I1C3=R
I	I	I	1	0
R	I	I	0.8	0.2
I	R	I	0.7	0.3
R	R	I	0.2	0.8
I	I	R	0.9	0.1
R	I	R	0.8	0.2
I	R	R	0.7	0.3
R	R	R	0	1

Conditional probability table of I2C3

B4 (TBC spallation)	C2 (combustor)	Probability of I2C3 (hot gas path failure)	
		I2C3=I	I2C3=R
I	I	1	0
R	I	0.8	0.2
I	R	0.7	0.3
R	R	0	1

C4 (bearing)

Conditional Probability Table of C4

A2 (lube oil system)	B1 (overspeed)	Probability of C4 (bearing)	
		C4=I	C4=R
I	I	1	0
R	I	1	0
I	R	1	0
R	R	0.001	0.999

C5 (AC pump)

Conditional Probability Table of C5

Probability of C5 (AC pump)	
C5=I	C5=R
0.001	0.999

C6 (emergency pump)

Conditional Probability Table of C6

The condition of A4 (digital control system)	The condition of A6 (UPS)	Probability of C6 (emergency pump)	
		C6=I	C6=R
I	I	1	0
R	I	1	0
I	R	1	0
R	R	0.001	0.999

(iv). Probability table of group D

D1 (rotor)

Conditional probability table of D1

C1 (compressor blading)	C3 (turbine blading)	C4 (bearing)	Probability of D1 (rotor)	
			D1=I	D1=R
I	I	I	1	0
R	I	I	0.9	0.1
I	R	I	0.9	0.1
R	R	I	0.3	0.7
I	I	R	0.9	0.1
R	I	R	0.9	0.1
I	R	R	0.9	0.1
R	R	R	0.001	0.999

D2 (compressor)

Conditional Probability Table of D2

C1 (compressor blading)	C4 (bearing)	Probability of D2 (compressor)	
		D2=I	D2=R
I	I	1	0
R	I	0.3	0.7
I	R	1	0
R	R	0.001	0.999

D3 (combustion chamber)

Conditional Probability Table of D3

C1 (compressor blading)	C2 (combustor)	Probability of D3 (combustion chamber)		
		D3=I	D3=R	
I	I	1	0	
R	I	1	0	
I	R	0.6	0.4	
R	R	0.001	0.999	degradation effect

D4 (turbine)

Original conditional probability table of D4

C1 (compressor blading)	C2 (combustor)	C3 (turbine blading)	C4 (bearing)	Probability of D4 (turbine)	
				D4=I	D4=R

Introduced intermedia nodes, then

Conditional probability table of D4

C2 (combustor)	C4 (bearing)	ID4 (mechanical failure)	Probability of D4 (turbine)		
			D4=I	D4=R	
I	I	I	1	0	
R	I	I	1	0	
I	R	I	1	0	
R	R	I	1	0	
I	I	R	0.95	0.05	
R	I	R	0.3	0.7	
I	R	R	0.95	0.05	
R	R	R	0.001	0.999	degradation effect

Conditional Probability Table of ID4

C1 (compressor blading)	C3 (turbine blading)	Probability of ID4 (mechanical failure)	
		ID4=I	ID4=R
I	I	1	0
R	I	1	0
I	R	1	0
R	R	0	1

Appendix B. The Dataset Converted from Multi-Attribute Technological Accidents Dataset

(Please see the excel file named Appendix B.)

The symbol ‘R’ represents ‘Regularly’, which means the component/factor/contributor works regularly (or normally), and no corresponding problem or failure is found.

The symbol ‘I’ represents ‘Irregularly’, which means the component/factor/contributor works irregularly (or abnormally). In other words, the corresponding problem or failure was indicated in the accident report.

Appendix C. Questionnaire for Dependence Analysis of Contributors to Construction Occupational Accidents

(Please see the Excel file named Appendix C)

Five tables were filled by five experts independently. Then the summary was developed by summing up the same box from the five tables.

- Strong-dependence

A score of 3 indicated a strong dependence when experts judged a contributor to be the cause of a consequence. For example, structural failure is likely to cause occupational accidents.

- Weak-dependence

A score of 1 indicated a weak dependence that experts postulated that a contributor might be a cause of the consequence, but they could not make a strong statement. For example, experts may suspect that a construction schedule or economic pressure might lead to a less optimal method statement.

- Non-dependence

A score of 0 indicated that there was no dependence on whether a contributor was viewed as the cause of a consequence. For example, experts may not believe that insufficient skills could cause physical problems for the worker.

Appendix D. Contributors to the Construction Occupational Accidents Dataset (CCOAD)

(Please see the excel file named Appendix D)

The symbol ‘R’ represents ‘Regularly’, which means the component/factor/contributor works regularly (or normally), and no corresponding problem or failure is found.

The symbol I represents irregularly, which means that the component/factor/contributor works irregularly (or abnormally). In other words, the corresponding problem or failure was indicated in the accident report.

Acknowledgements

Firstly, it is with immense gratitude that I acknowledge the extremely friendly, professional, and valuable guidance from Professor Michael Beer, throughout my research period at the Institute for Risk and Reliability (IRZ) at Leibniz University Hannover (LUH). I could not think of a better advisory and mentoring research supervisor for any Ph.D. candidate! I appreciate all the knowledge opportunities, discussions, and insightful comments, which helped me broaden my views from numerous perspectives and develop new ideas to face future challenges in the risk and uncertainty fields and life.

I would like to thank Dr. Matteo Broggi, for the massive knowledge and valuable advice on the mathematic aspects of my research life in IRZ.

I am very thankful for the support given by Dr. Holger Zimmermann, who give a huge contribution to developing the example model brought into this research project.

The insights from the Chinese construction industry and academia, which had the hard task to assist in developing the construction failure model, were extremely useful and added great value to my work, and I want to show my deepest appreciation to all of them, particularly to Mr. Yinjun WU, Mr. Yongbin PEI, Mr. Yu WANG, Mr. Shengsheng SHENG, and Professor Wei WANG.

It is an honor for me to express my deepest appreciation to my wife Xin KANG and my little daughter, who encourage my research journey and joy in my life.

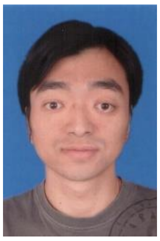
I am eternally indebted to my parents Lianrong WANG and Yongxian ZHUGE (in memoriam). Your example of love, sacrifice, fighting, and wisdom will guide my life forever and will always motivate me to achieve my objectives with honesty, passion, and enthusiasm.

Finally, I would like to thank my fellow colleagues at the Institute for Risk and Reliability. They helped me settle down in Hannover. They made me feel warm when I was 9,000 kilometers from home. All the research and fun we had in these years will

never be forgotten; my Ph.D. experience was surely enhanced by the terrific work environment you have always sustained!

Curriculum Vitae

YANG WANG



PhD Candidate
Chartered Consultant Engineer of Railways and Infrastructure Projects, China
Institute for Risk and Reliability, Faculty of Civil Engineering and Geodetic Science, Leibniz Universität Hannover (LUH).
Callinstr. 34, 30167 Hannover, Germany
Email: yang.wang@irz.uni-hannover.de

Education

04/2017-present **PhD. Candidate in Civil Engineering**
Leibniz University Hannover, Germany

09/2005-06/2008 **M.Eng in Disaster Prevention and Risk Reduction**
Central South University (CSU), Changsha, P. R. China

09/2001-06/2005 **B.Eng in Engineering Mechanics**
Central South University, Changsha, P. R. China

Work Experience

07/2008 – 03/2017 **Research Associate (Permanent) and Principal Consultant Engineer,** China Academy of Railway Sciences (Shenzhen) Research and Design Institute Cooperation Limited, Shenzhen, P.R.China

- *09/2016 - 03/2017* **Chief Consultant Engineer.** I was in charge of the Tinghai road infrastructure construction supervision in Qianhai Shenzhen-Hong Kong Modern Service Industry Cooperation Zone. I was in charge of a team of 20 personnel to supervise the progress of the construction. Quit the job for personal reason and started my PhD project in 04/2017.
- *12/2015-03/2017* **Project Manager**. I was leading four colleagues to develop a software to provide standardized records for the supervision of infrastructure projects. I have sketched the blueprint of the system for its PC and mobile versions.
- *12/2013-09/2016* **Associate Chief Consultant Engineer**. I worked at the Xintang section (about 25.8km, including 4 stations and 11 bridges) Guangzhou-Dongguan Intercity Railway. I was in charge of a team of 25 personnel to supervise the progress of the construction. I have been coordinating with investors, contractors, and local authorities.
- *05/2010-12/2013* **Consultant Engineer.** I worked closely with the Chief Consultant Engineer to supervise the construction of Shenzhen section (about 33.3 km, including 8 bridges, 6 tunnels, and 5.4 km of roadbed) in the Xiamen-Shenzhen High-speed Railway Project. I was in charge of inspecting the quality and safety assurance system, to check the finance reports submitted by the contractors, to record and report quality and safety issues, and to draft periodical quality reports.
- *07/2008-05/2010* **On-site Consultant Engineer.** I supervised the construction of the Dongjiaotou Station on Line 2 of Shenzhen Metro. I inspected the construction of deep foundation pits and reinforced concrete structures and assisted to supervise

the shield tunneling work between Dongjiaotou Station and Shuiwan Station, to monitor the quality of materials and to collect diving data.
- *03/2011* Received training in supervision and management of high-speed railway projects by SYSTRA (Shanghai) Consulting Co. Ltd.

Research Projects

04/2017-01/2020 Influence of Human Error in Infrastructure Projects
- Supervised by Prof. Michael Beer
- Collected hundreds of accident cases during building process in construction industry (mostly in China), then developed a Bayesian Network model based on the dataset combined with expert knowledge to analyse the influence of human error in construction building process

06/2007 – 04/2008 Structural Risk Assessment of Tunnels under Fire Load for Ningbo-Taizhou-Wenzhou Expressway
- Supervised by Prof. Zhisheng XU and worked with Zhejiang Provincial Institute of Communications Planning Design & Research
- Used the ANSYS and FLAC3D (with the two-dimension plane numerical simulation) to numerically model tunnel lining safety performance of three tunnels under fire load and proposed a method to assess tunnel lining under fire load by evaluating how the section with the highest temperature deduct its stiffness, calculating the internal force, and analyzing stabilization of the tunnel. The proposed method provides a feasible way to assess the structural safety of tunnels after fire disasters.

06/2007 – 09/2007 Fire Resistance Assessment of the Guangzhou Airport
- Supervised by Prof. Zhisheng XU and worked with Tianjing Fire Research Institute
- Completed the mechanical analysis of the airport's steel structure under fire load based on the thermal-mechanical coupling theory and with the finite element method by using ANSYS.

05/2006 – 07/2007 Risk Assessment of Shiziyang Tunnel of Guangzhou-Shenzhen High-speed Railway
- Worked with Dr. Wei Wang and China Railway Siyuan Survey and Design Group Co. Ltd.
- Assisted Dr. Wang to analyze risk of disasters during its operation period, especially the fire, earthquake, explosion and derailment. My specific responsibilities included collecting data of constructions damaged by similar accidents, then calculating the risk probability and the loss.

Qualifications

Chartered Consultant Engineer of Railways and Infrastructure Projects, P.R China
Consultant Engineer Qualification of Railway Construction
Consultant Engineer Qualification of Shenzhen City

Awards & Honors

2011 **The Locomotive Medal** (the highest honor awarded by the Railway Workers' Union, China)
2005 **Outstanding Graduate of Central South University** (for top 5% of students)