DERAILMENT RISK ANALYSIS, MONITORING AND MANAGEMENT AT RAILWAY TURNOUTS

by

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Abstract

The general objective of the thesis is to develop a number of novel Bayesian-based mathematical models that are applicable for the railway sector. Hence, it is assumed that the thesis will be an element of, or facilitate future AI (Artificial Intelligence) Risk Management and Safety Standards, which will inevitably be developed for the sector. The thesis primarily concentrates on applications that support decision-making processes, related to derailments at railway turnout system. The first objective is to determine, evaluate and prioritise the risk factors that cause derailments; secondly, it will identify and demonstrate the relationship among these driving factors; and finally, it will show the prospective usage of Bayesian networks as an intuitive modelling instrument that makes the process of modelling risk more transparent and consistent.

In order to achieve the aforementioned objectives, this thesis is established on various novel methodological approaches using either qualitative or quantitative methods, or a combination of the two. A comprehensive review is conducted in order to interpret and acquire an in-depth understanding of suitable methods of analysing risk in addition to five original studies on the subjects of component failures, human errors and the environmental impact to measure, rank, categorise, and identify the factors that cause derailment in the railway sector.

The proposed novel methodologies in addition to their MATLAB and R codes are introduced for utilisation in a developed framework for analysing, monitoring and managing risk for railway turnout.

Dedication

This thesis is dedicated to my beloved mother, father, brother and to my beloved wife Ceren, and my sweet daughter Derin Ece.

Declaration

This thesis is a presentation of my original research work. Wherever contributions of others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgement of collaborative research and discussions.

The work was done under the guidance of Dr Sakdirat Kaewunruen at the University of Birmingham, the UK and Dr Min An at the University of Salford, the UK.

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I gratefully acknowledge the Turkish Ministry of Education for supporting my PhD at the University of Birmingham. Additionally, my work is funded by the European Commission under the financial sponsorship of the H2020-RISE Project No. 691135 "RISEN: Rail Infrastructure Systems Engineering Network", which enables a global research network for tackling the immense challenge of the resilience of railway infrastructure and advanced sensing in extreme environments (www.risen2rail.eu).

I also thank RAILTEC group members for their assistance during the course of this comprehensive research; particularly Christopher P.L. Barkan, who provided many useful discussions and the oficial railway accident database.

Finally, I thank my family for all their love and encouragement. To my parents who encourages my love of science and supported me in my pursuits. But mostly for my loving, supportive, encouraging, and patient wife Ceren, for her faithful support during the final stages of this Ph.D., and who takes lovely care of our beautiful baby which is so appreciated. Thank you.

Publication List

This thesis is predominantly constituted of an extended comprehensive summary and the following significant scientific developments in the research domain:

Paper A: Dindar, S., Kaewunruen, S., & An, M. (2018). Identification of appropriate risk analysis techniques for railway turnout systems. *Journal of Risk Research*, 21(8), 974-995.

Paper B: Dindar, S., & Kaewunruen, S. (2017). Assessment of turnout-related derailments by various causes. *Sustainable Civil Infrastructures: Innovative Infrastructure Geotechnology* (pp. 27-39). Springer, Cham.

Paper C: Dindar, S., Kaewunruen, S., An, M., & Sussman, J. M. (2018). Bayesian Network-based probability analysis of train derailments caused by various extreme weather patterns on railway turnouts. *Safety science*, 110, 20-30.

Paper D: Dindar, S., Kaewunruen, S., & An, M. (2018). Bayesian based-Human Error Probability Assessment of Derailments at Different Kinds of Switches and Crossings, *submitted*

Paper E: Dindar, S., Kaewunruen, S., & An, M. (2019).Bayesian-based hierarchical model for analysis of climate on hazardous railway component failures, *submitted*

Paper F: Dindar, S., Kaewunruen, S., & An, M. (2019). Rail accident analysis using large-scale investigations of train derailments on switches and crossings: Comparing the performances of a novel stochastic mathematical prediction and various assumptions. *Engineering Failure Analysis*, 103, 203-216.

Contributions of the Appended Papers to the Thesis

Six of the published papers that are appended were prepared in collaboration with co-authors. The summerised contributions to these papers by the author of this thesis are as follows:

Paper A: Identified what methods are proper to this study.

Reviewed the previous studies associated with risk analysis in engineering systems.

Paper B: Investigated derailments accidents taking place at rail turnouts.

Categorised and then prioritised in accordance with the proportion of train derailments occurring within each category of derailments drivers.

Paper C: Proposed a novel risk analysis based on railway turnout systems under uncertainty of all weather and environmental conditions effecting particular locations.

Investigated then causal relationships between weather patterns and derailments on the systems to enlighten rail operators.

Paper D: Established a unique human error-based Bayesian network to facilitate the quantification of uncertainties in the management of switch and crossing-operation.

As a result, prioritized over 50 human-errors, and make a number of critics and suggestion on monitoring and managing the risk of the derailmen.

Paper E: Established a new stochastic mathematical prediction model on the basis of a hierarchical Bayesian model (HBM) to deal with derailments on a large-scale analysis.

Proved the suggested methodology must be followed for the further studied in the domain.

Paper F: Argued that there are differences in the various mathematical assumptions used as risk indicators

Used both these and recorded observations in a derailment risk analysis which concentrates on component failures at RTs.

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CHAPTER 1

INTRODUCTION

1.1 Background

1.1.1 General view

Train derailment is an undesirable accident causing damages to both rolling stock and infrastructure as well as service disruptions, and which might also cause casualties and harm the environment. Moreover, these effects might result in serious reputation and financial losses to railway companies and organisations, as well as social, pshchological and economic consequences to the public.

Although EU members have claimed that train operating safety is constantly improving and the number of derailments across the EU has been slightly reduced, there appear to have been around 500 derailments per year in the last ten years, of which 7% (35 derailments) involved catastrophic consequences (Robinson et al., 2012). On average, catastrophic derailments potentially result in 30 fatalities per year, each of which costs, approximately 10M£ (Vasić et al., 2014).

ERA (European Railway Agencies) points out that various infrastructural problems, e.g. track geometry faults and switch faults, account for 70% of all causes of derailments across the EU members. Moreover, the majority of such derailments is claimed to occur at railway turnouts (ERA, 2008). This is because railway turnouts themselves as all of complex engineering systems are inherently and unavoidably hazardous by the own nature. The frequency of hazard exposure can sometimes be changed but the processes involved in the system are themselves intrinsically and irreducibly hazardous. It is the presence of these hazards that drives the creation of defenses against hazard that characterize these systems.

Network Rail, the owner and infrastructure manager of most of the railway network in Great Britain, has 21,000 track miles and 19,000 turnouts (Dindar et al., 2017). In other words, it can be said that there is one turnout per 1,14 track mile in the UK. As a result, a large number of derailments, statistically accounting for 46% potentially higher-risk train accidents over the last 10 years, has occurred at turnouts in the UK (RSSB, 2009). Causes of a derailment are often track and turnout component failures, malicious operational failures, loading faults, environmental conditions, human factors, interaction problems or a combination of them.

This section commences with an explanation of railway turnouts and the variety of commonly used risk methods applied in railways. Subsequently, it proceeds with descriptive reviews on the fundamental elements of turnouts to form a thorough understanding as well as to construct an analysis between them and research based on risk. This section then focuses on the subject of derailment by establishing possible risk factors that could be connected. Next, stages within risk management are determined, analysed and considered within the thesis scope.

1.1.2 Railway turnout

Turnouts in the railway system, alternatively called switches and crossings in European vernacular, are comprised of a mechanical railway system that consists of two or multiple movable rails whose function is to guide railway vehicles on their designated route (see Figure 1.1). The considerably complex nature of railway turnouts has led to emerging operational risks for railway networks. (Chandra et al., 2008). This has been demonstrated by the increasing amount of derailed trains on or close to railway turnouts (FRA, 2016). These accidents generate operational interruptions and financial damages, and occasionally even deaths. A suitable estimation of the type of risks inherent to systems of railway turnouts is necessary for those responsible for managing railway systems so that the whole railway network can function while interconnecting with different infrastructures of railway. As a result of the increasing amount of strain placed on railway networks, the management of risks associated with railway turnout systems will necessitate more in-depth examination to provide a concrete railway operation.

Turnouts on railway systems are fundamental components of any interconnected railway network. The transition of a train from one rail to another is achieved through the use of turnouts. In general, they comprise approximately 30% of the overall budget allocated to maintaining and constructing railway systems, which equates to around 0.3km of 1 km regular plan track (Dindar and Kaewunruen, 2017). Within the European Union, it is estimated that countries have installed turnouts at a rate of slightly more than one turnout per kilometre of rail (Ishak et al., 2016). Therefore, it is expressed that railway industry should always target improvement of safety measurements as railway turnouts are pivotal infrastructures.

1.1.2.1 Parts of a turnout

Railway turnouts are largely constructed with a variety of specific elements that are grouped into three different categories of turnouts, and commonly used parts are incorporated into those categories.

Switch panel

The function of a switch is to manage the direction in which traffic processes on the direct or diverging stretch of track. Normally, it is composed of movable switch blades (number 1, see Figure 1.2) that change the direction of the train as required. The movement of the blades is achieved through bearings or slide bars that are attached to the stock-rails and are held securely in place via a locking

Figure 1.1: A left-handed turnout illustration

mechanism.

Closure rail

A closure rail (intermediate track) is the component of the turnout that forms a connection between the switch and the crossing area. It is generally comprised of a total of four rails (number 2, see figure 1.2) that have the ideal curved shape that enables the transitive geometric attributes of the turnout to be maintained. Normally, the intermediate track includes isolating joints in the diverging line.

Crossing panel

Crossing panels are significantly important elements of turnouts, as they are the only part of the system in which there is a discontinuity in the line. The

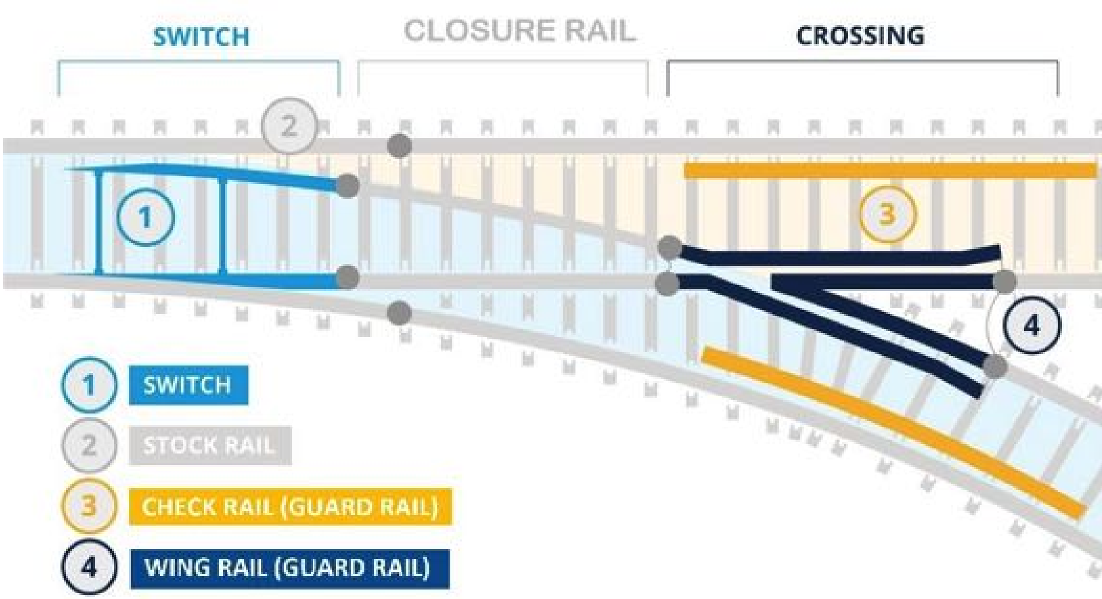

Figure 1.2: Fundamental areas and parts of a railway turnout

purpose of the crossing is to ensure that the wheels are correctly guided when traversing and trailing the intersection. The crossing area allows for wheels to travel along both intersecting paths. In order to guarantee this, guard-rails (number 3 - 4, see Figure 1.2) are utilised to enforce a constrain on the passing wheelsets from moving laterally. This is to avoid the derailment of rail vehicle.

1.1.2.2 Component definition

The different components of turnouts are illustrated in Figure 1.3. A brief summary of each part in addition to its technical description is given below.

- Stock rail: the primary rail of the track on which the switch blades are tightly positioned
- Points (alternatively called switches): Steel blocks constructed by the mixture of a pair of stock and switch blades along with the essential linkages and components

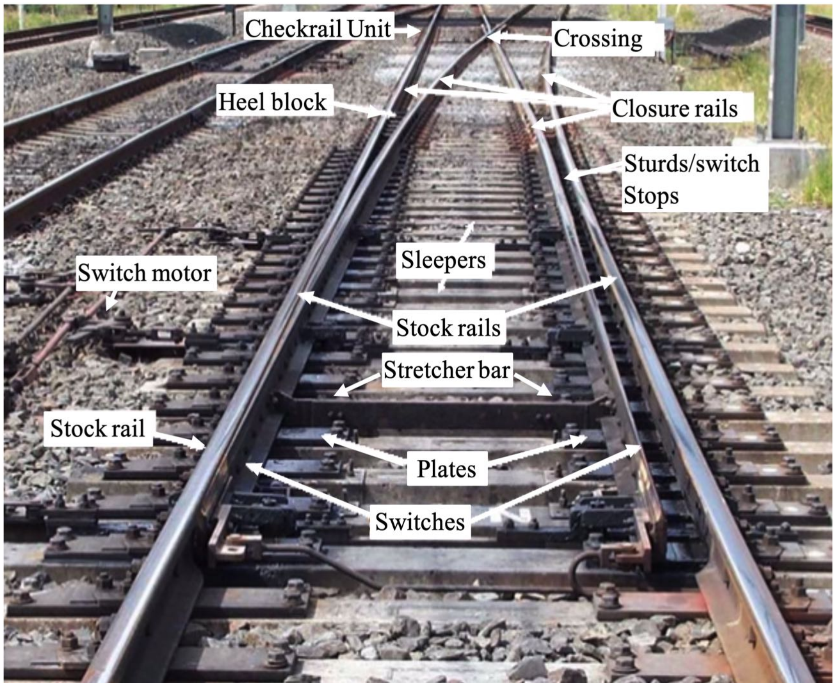

Figure 1.3: Fundamental components of a turnout (Dindar et al., 2016)

- Crossing nose: a composition of rails incorporated at the junction where a pair of rails intersect, which enable a vehicle's wheel flange to be transitioned between tracks

- Switch Motor: a system that runs on electric, hydraulic or pneumatic power that is utilised in the alignment of the switch with one of the potential tracks

- Stretcher Bar: a steel bar utilised to ensure that the switch rails are correctly positioned under a moving vehicle

- Sleepers: they in general are situated in a perpendicular manner to the rails and function by transferring loads from these rails to the track ballast and subgrade. Their additional advantages are that they maintain the upright position of the rails and ensure that the track gauge is appropriate.

- Closure rail: the element of a fixed rail that is situated between the points and the crossing of a turnout to facilitate the transition of a railway vehicle from the switch panal to the crossing panel

- Heel Block: a unit that delivers a splice with the adjacent closure rail and a location for the switch point rail

- Check Rail: a short piece of rail situated adjacent to the stock rail opposing the crossing to guarantee that the suitable flange way through the crossing is trailed by wheels

1.1.2.3 Turnout operation

The functioning of a railway switch is generally achieved through one of two ways: either manually by an individual operator (hand-operated switch) or a radio-controlled electric motor via hydraulic or pneumatic actuation. Before the broad prevalence of radio-controlled electric motors that can automatically transfer the switch system between positions, as illustrated in Figure 1.3, it was common for switches to be operated manually either by a member of the train's crew or a dispatcher. In fact, one can even still observe this kind of operation being used on railway networks in various developed nations. The use of a switch motor that adjusts the points in line with one of the potential tracks via mechanisms powered by electric, hydraulic or pneumatic means is now widely used on railway systems and the only input from human operators is from dispatchers located in central offices. One of the general characteristics of the motor is detection as to whether the switch is totally locked or set and informs the dispatchers accordingly. In circumstances involving switch failure, the railway signal changes to red, indicating that no train is permitted to move further on that specific stretch of track. In certain infrequent instances, a member of the train's crew can manually intervene by utilising a handle to alter the position of the switch that is usually controlled remotely in order for the train to proceed; however, such actions are generally prohibited.

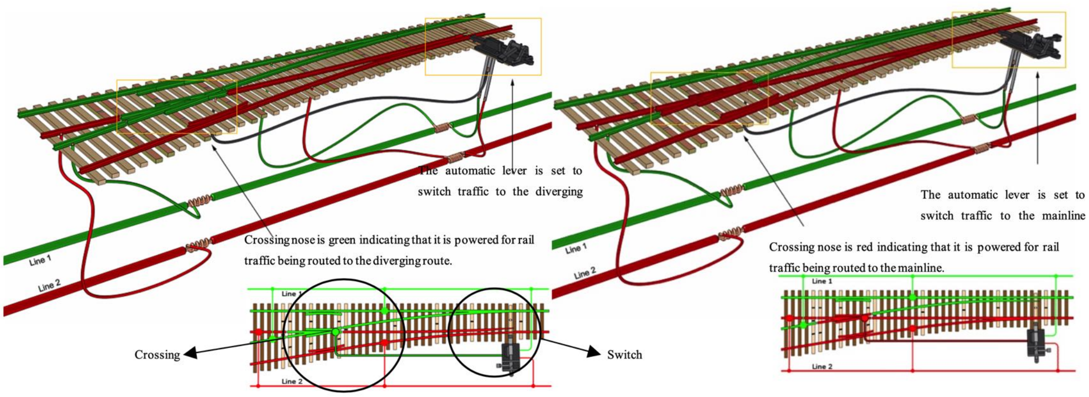

Figure 1.4: The mechanism of a simple radio-controlled turnout

Conversely, particular kinds of switches (i.e., spring and weighted switches) rely on the train weight and the wheel flanges to move the switch in a natural manner when the train traverses the switch[1]. Spring switches permit to traverse the reverse section of the switch in the trailing point[2] direction apart from the standard route when traversing in the facing points[3] direction.

1.1.2.4 Discussion

An overview of the important results in this section is presented here with a description of the basic components and subsystems of a turnout system. Various figures illustrating these components (i.e., switch blades and the associated subsystems, turnout switches) are included in order to form macro-based associates between components and micro-based between subsystems. Additionally, the types of turnout operation that are frequently utilised are identified. This identification will be used in Chapter 2.

[1]All these kinds of passive switch mechanisms are referred as spring switches.
[2]A set of points at which two routes converge in the direction of travel.
[3]A set of points at which two routes diverge in the direction of travel.

1.1.3 Derailment

The technical definition for a derailed train at a turnout is where the railway vehicle runs off three kinds of rails (indicated as 1-3 in Figure 1.2). The risk of derailed trains is still elevated for governments and rail companies operating in both developed and developing countries. An average number of 71 incidents of derailments are recorded in the UK on an annual basis[4], which accounts for approximately one-seventh of the total incidents within the EU (Tucker et al., 2014, Vasic et al., 2012). Based on the findings of a report published by D-Rail (Ibid), around 7% of all derailments that occur in the EU involve deaths, significant injuries and costs. On average, there are two deaths annually with the resulting costs of such incidents amounting to approximately £100 million.

Train derailments could be attributed to any of the below primary indicators and factors:

- Component failure, poor maintenance or design (Wolf, 1998)
- Various human errors (Baysari et al., 2008)
- Poor moving, loading loads and poor securing of loads (RAIB, 2006)
- Operational failures (Vernez and Vuille, 2009)
- Environmental factors (Bearfield and Marsh, 2005)
- Derailment criteria:

  Wheel unloading (Garg and Dukkipati, 2012)

  Flange climb (Wu and Elkins, 1999)

  Lateral / Vertical force ratio (Wu and Elkins, 1999)

[4]The figure is assumed without considering whether occurrence has financial loss or fatality.

- Wagon Track dynamics:

  Hunting (Hay, 1982)

  Roll and sway (Garg and Dukkipati, 2012)

  Wagon bounce (McClanachan et al., 2002)

- Train Wagon dynamics:

  Forces due to longitudinal vibration (Duncan et al., 1989)

  Steady state force (Duncan et al., 1989)

  Impacts (Duncan et al., 1989)

  Vertical and lateral jack knifing (El-Sibaie, 1993)

  Wagon pitch (McClanachan et al., 2000)

  Bogie pitch (McClanachan et al., 2000)

- A combination of these factors

It is observable that the fundamental causes of the problem of train derailments are exhaustive and have a certain interconnectedness. For example, the assumption could be made that the cause of an occurrence of derailment is a problem with the signals; nevertheless, it is possible that this signalling error could also be directly related to human errors as a result of substandard training or deficiencies within the organisation, such as excessive work(Wilson and Norris, 2005).

The thesis reasonably addresses the most significant factors involved in the phenomenon of derailment. The scope of the thesis does not include train dynamics and wagon-based failures, as civil engineering-oriented factors e.g, infrastructure failures, operational failures will be examined. That is, the primary subject is the failure of components that are predominantly the causes of train derailments at turnouts. Nonetheless, certain other factors that are considerably responsible for derailments will also be addressed and connected to the scope of the thesis accordingly.

1.1.3.1 Discussion

This section of the Chapter 1 concentrates on the primary indicators and factors that cause train derailments at turnouts, with specific references to studies in the literature. As observed, the fundamental causes of derailments requires comprehensive studies and there are certain connections linking them. For example, the assumption could be made that the cause of a derailed train is a faulty signal. Nevertheless, the factor that originally caused this signal error may have been human error resulting from inadequate training or organisational deficiencies, such as excessive work. Thus, it is clear in the literature that there is a lack of topological risk networks for railway turnouts. This thesis aims to fill this gap in the literature.

Additionally, this section makes reference to the holistic causes of derailment, acquired from multiple different sources. Nevertheless, it is acknowledged that their studies are not purely focused on railway turnout systems and the kinds of accidents that may occur have not been categorised. Thus, this thesis will endeavour to fill this gap too and this study will be addressed in Chapter 3. Conversely, there is no consensus in the literature regarding the specific factors that impact deterioration and turnout component failures, such as type of traffic, density of traffic, and operational conditions. These factors will be studied via a group of novel methodologies in Chapter 6 and 7.

1.1.4 Risk management framework

In the context of risk management related to the railway industry, a variety of different terms are often utilised in the description of specific scenarios or occurrences. The section below will outline some of these terms and their accompanying definitions.

1.1.4.1 Hazard

According to the HSE[5], a hazard is a phenomenon (e.g., an item, substance characteristic or action) that has the potential to lead to detrimental impacts(Lees, 2012). For example, it is possible that a sharp blade profile would be categorised as a hazard as it could potentially lead to derailment, which is therefore defined as a detrimental consequence.

Therefore, the appropriate determination of hazard is considered to have importance in the minimisation or eradication of the detrimental effects of hazards. According to Workcover (WorkCover, 1996), suitable identification of hazards can only be accomplished by understanding the characteristics of hazards within the work environment. Consequently, it is imperative that the origins of hazards and the manner in which they materialise are comprehensively understood. The process of identifying hazards incorporates the analysis of all possible sources of hazards as well as the history of previous related incidents. The following chapters will provide an explanation of both these parts of the process

1.1.4.2 Accident

In general, an accident is defined as an undesirable incident that causes individuals to experience physical harm (to health or life) or damage to property.

[5]Health and Safety Executive

Even though there is general agreement regarding whether an accident can be considered as an unintended occurrence, the word 'incident' is often utilised to define occurrences that that do not cause injuries (Dixit, 2006). Nevertheless, incidents are frequently perceived as warnings that had not previously been regarded as such (Stringfellow, 2010).

Accidents have a particular importance when performing any form of risk analysis, particularly in the situation where the outcomes of the accidents are examined on the basis of measures of accidents. Accidents regarding engineering systems, such as railway turnouts, frequently have various unique interrelated causes.

1.1.4.3 Risk

Risk is defined as the probability that a hazard will cause an accident, which leads to causalities like damages to property, negative financial impacts or even death (McNeil et al., 2015). Hence, it is possible to statistically determine the risk as a probability of an unwanted occurrence or adverse outcome of an incident. In the context of engineering, risk is generally defined as (Henley and Kumamoto, 1981):

$$Risk = Probability\, of\, a\, failure * Damage(severity) \tag{1.1}$$

It is possible to rephrase Eq. 2.1 as the probability of an accident and losses (both financial and human) for each accident. The multiplication of both leads to risk. It could instantly be believed that the likelihood of a category of failure and its associated impact should be identified to determine the level of risk (Summala, 1996). Nevertheless, instances of derailed trains at railway switches do not occur frequently, while according to the Office of Safety Analysis, the financial ramifications can be range from the thousands to millions of US dollars (FRA, 2016). Moreover, the average cost for each incident involving the derailment of a freight train is reported to be between 390,000 euro and 1,402,000 euro(CORDIS, 2015). Due to the fact that this thesis aims to identify and prioritise levels of risk based on derailment causes, it is likely that the wide range of damage estimations and the differences between sources of data will produce non-viable outcomes. For example, in the last 10 years, a total of five trains have derailed due to particular adverse weather events. However, the costs resulting from the most recent incident were over 2.7 times greater than the other three occurrences. Hence, this leads to the question regarding what would have been outcome if this research had been completed one year ago. Thus, it is important to note that this thesis adheres to a principle the risk approaches the likelihood of failure in infrequent events(Woodruff, 2005).

The most widely used method in general depends on the observed frequency of the incident when consequences vary. However, it is not possible to apply this approach to events that occur rarely as, per the definition, they occur infrequently and it is necessary to collect a sizable dataset if the resulting estimates are to have good reliability (Montgomery and Runger, 2013). As an example, for events that happen only once every 10 years, it is necessary to gather data from a few previous decades in order to acquire estimates that exhibit strong reliability. Alternatively, the existing quantitative data of 10 years could be combined with expert opinions where further quantitative data is not available (Paté-Cornell, 1996). On the other hand, another approach that involves the enhancement of the precision of estimates of infrequent events is the generation of sample events (Glynn and Iglehart, 1989, Heidelberger, 1995). Subsequently, it is possible to extrapolate the sample event's frequency to the rest of the scenario in a manner that is proportional to how narrowly the sample was taken. This process is widely defined as importance sampling and requires data to be sampled from scenarios in which it is expected that the infrequent event will occur. Conversely, it is observed that a number of different studies have relied on experts in the field to determine event probabilities(Chen et al., 2000).

This thesis will utilise both of the approaches explained above. In situations where formal data is not required, the approach taken involves either opinions from experts or sampling techniques.

1.1.4.4 Risk management

As seen in Eq. 1.1, calculating risk can be a complex task as it is necessary to make estimations of the likelihood of failure and potential damage. Furthermore, the technique of examining the relationships among risks can also present certain complexities (Blockley and Blockley, 1992). Consequently, a variety of different techniques have been utilised by researchers to evaluate and calculate risk, such as tree analysis and fault tree analysis. In the subsequent chapters, this thesis will investigate the extent to which these techniques are compatible with the scope of the research.

Risk is a phenomenon that can be managed. It has been emphasised by the BSI[6] that the management of risk involves the methodical implementation of management policies, processes and practices to the actions of examining, assessing and managing risk (International Organization for Standardization, 1996). The Proposed Risk Management Cycle (RMC) is shown in Figure 1.5 (Baker et al., 1999).

Despite the fact that BS4884-3:1996 does not clearly emphasise every suggested phase in the Figure 1.5, the definitions proposed by Scott et al. (Baker

[6] The British Standards Institution

Figure 1.5: Risk management cycle

et al., 1999) are summarised below:

I. Risk Identification is formally defined after the identification of a specific hazard. In the event that a distinguished hazard is eradicated and/or its ramifications are considered to be insignificant, it is possible that the analysis could be terminated.

II. The outcome of Equation 1 is Risk Estimation. Hence, it is important to calculate both the frequency of a hazard event and the severity of associated consequences with minimal errors. The regularity and level of seriousness are frequently determined by using either qualitative or quantitative techniques. Both such approaches will be examined in the following chapter.

III. Risk Evaluation determines whether the risk requires appropriate action or

[7] Risk tolerance remains an area of development in the railway sector. For example, both rails and axles are critical elements, because any deficiency could lead to disastrous derailments. Nevertheless, in certain situations, it could be determined that a risk is deemed to be unacceptable based on the cost-benefit analysis (Zerbst and Beretta, 2011).

is deemed tolerable[7]. This phase is completed by utilising quantitative or qualitative techniques, or a combination of the two.

IV. Risk Response incorporates risk prevention or eradication, retention, transferal and reduction.

V. Risk Monitoring identifies whether the actions taken are achieving the appropriate results during the entire lifecycle of the part, mechanism or process.

Each of these stages is also formulated and included in a developed and thorough flow chart that will be illustrated in the future work section. The risk response actions are explained in greater detail below (Cameron and Raman, 2005, Merna and Al-Thani, 2011).

Avoid: Eradicate the risk of train derailment in order to offer protection to the turnout functionality from its impacts. The following is a list of frequently applied practices that can eradicate such risks.

- Alter the project's scope (i.e., condition monitoring procedure)[8]
- Adjust deadlines to remove the risk of timely project realisation (i.e., substantial engineering work)
- Provide clarification on specifications to eradicate uncertainties and misinterpretations (i.e., regulations)
- Increase proficiencies to eliminate technical risks (i.e., training for railway employees)

[8]The procedure that involves the monitoring of a parameter of condition in rail constituents so as to determine any significant changes, which are indicators of emerging faults.

The condition monitoring procedure could have been implemented into the Chapter 4 and 5. Nevertheless, due to the specific nature of this thesis, only failure of components that cause train derailments at railway turnouts have been analysed. Due to the fact that such incidents only account for a small proportion of failures that impact service, the incorporation of the studies into a widely utilised condition monitoring approach would be an inefficient use of time, would produce unviable outcomes and would not be possible to implement in an industrial setting as a result of the cost benefit analysis. In a similar manner, lengthening the time period allocated for railway maintenance would be an unfeasible option from the perspective of railway companies due to the increased burdens accompanied with minimal gains. Conversely, in situations where outcomes are not satisfactory, it is important that existing regulations are modified. For example, in 1997, Railway Safety Regulations were updated, where some of the existing regulations had not been changed since 1839. Based on the conservative framework in which the railway sector operates, the objective of this thesis will not be to alter any specific regulation, but to offer novel recommendations to the sector. For instance, training for railway employees could an alternative to other approaches to risk response. Chapter 5 will focus on human errors, identifying the employee groups most at risk and the errors with which they are associated ordered from most frequent to least frequent.

Transfer: This is where the effects of the risk are transferred to an external entity. Direct approaches could include the utilisation of insurance, guarantees or contract bonds. On the other hand, indirect approaches might be unit price contacts rather than lump sum (or the opposite contingent on the side of the contract the party is on), legal assessments, among others. Employing a subcontractor to complete a certain stage of the task is another method of transferring risk, although it is important to obtain assurances that the contractor has the capacity to manage the risks in a more effective manner. As can be observed, this approach is strongly connected with each of the rail parties agreeing to a contract. This thesis will not apply any focus to any conflicts that could emerge between separate parties prior to or subsequent to a case of derailment as it will primarily concentrate on quantitative methods (i.e., mathematical modelling). Conversely, a variety of different techniques have thus far been described in the literature (Chung, 2016, El-Sayegh and Mansour, 2015, Gatzert and Kosub, 2016, Nguyen et al., 2018). Most of these studies can be implemented in reference to the transferral of derailment risk between parties. Rather than presenting a repetition or making minimal adjustments to previous research, the thesis aims to devise innovative concepts in the field. Accordingly, it does not endeavour to transfer the risk itself.

Mitigation: This involves reducing the likelihood or the effects of the risk. However, this cannot always be achieved and frequently incurs costs that should be weighed against the benefits of implementing the mitigating activity. This thesis will only apply this approach in Chapter 5 with a focus on human errors.

Accept: There are inherent risks in all kinds of engineering projects. At the baseline level, one must consider the risk that the project will not achieve its overall aims. Hence, as the definition implies, stakeholders must be willing to accept a certain level of risk. The acceptance of risk should be considered like all other strategies, meaning that it should be accompanied by appropriate documentation and communication. Risk can be accepted either passively, implying that the outcomes are managed subsequent to the materialisation of the risk, or actively, where contingent plans are incorporated into the project to cover any potential outcomes of the risk. For instance, Chapter 4 presents the effects of enviromental reasons on component failure, thus emphasising that certain climate areas have specific effects on components of the system. Thus, it is not possible to demand that these rail components not be utilised in these areas. Furthermore, it is not recommended that that the railway be built in a different area. Therefore, the risk of derailment must naturally be accepted by the railway stakeholders.

The final stage of the process is Risk Monitoring, whereby railway stakeholders and members of the project team continuously monitor the system to allow new and developing risks to be identified and controlled and that appropriate response actions are implemented effectively. This process will continue throughout the lifecycle of the rail track. Consequently, this thesis will adopt updatable risk analysis methods (posterior probability in Bayesian analysis). This allows risk monitoring and control to effectively oversee the determined risks, residual risks and emerging risks. The bayesian based methodologies are addressed to the research gaps, revealed in Section 1.3, throughout Chapter 5 to 8. Additionally, it facilitates the supervision of the implementation of prepared strategies for the determined risks and to assess their degree of effectiveness.

1.1.4.5 Discussion

The existing concept of risk management in the railway sector is addressed in this section. Additionally, the basic terminology is presented. The Fundamental Concepts of Risk Analysis assesses and evaluates two kinds of concepts that exist in risk analysis, namely quantitative and qualitative. Nonetheless, all current techniques of analysing risk, such as FTA, ETA, Markov analysis, risk matrix, FMEA, Reliability Block Diagram, Hazard Function and Bayes Analysis are not included as there is a lack of research that has focused on their advantages and disadvantages in practice. Moreover, it was not always possible to find appropriate examples in the literature that would demonstrate the association between incidents of derailment and these particular techniques.

It can be observed that there is a considerable gap in regard to which techniques are appropriate for turnout subsystems. This represents a crucial step in the process of identifying and defining any risk(s) connected with a particular decision and then assessing all possible results and effects of that risk. Additionally, PhD theses on the subject of risk management in the context of railways appear to only present the holistic benefits of the techniques with no comparison to other methods to determine advantages. To fill this gap, Chapter 2 will be investigating what risk analysis methods are appropriate to railway turnouts.

1.2 Research Problem

Current risk analysis tools are often intended to concentrate on all hazard types (e.g. derailment hazards, collision hazards, fall hazards, fire hazards, slip/trip hazards, electrocution hazards, train strike hazards and platform/train interface hazards) and the railway risks as a whole system, regardless of the distinguishing characteristics of the systems forming the railway and hazards, resulting in different consequences. Nevertheless, the ability to manage a specific hazard occurring within an individual system, such as derailments at turnouts, would facilitate more accurate failure estimation and would provide the opportunity to establish more effective maintenance approaches for diminishing the risks levels related to the specific hazard within the specific system.

Risk analysis reliability is based on the following factors

- The level of reliability and credibility these models have for turnout operations in terms of the development of strategic risk priorities
- The capacity to further develop these models, to help railway companies, to identify and justify their strategic risk priorities

It has been determined that ALARP and top event techniques by LU[9], RSSB[10] and Network Rail[11] do not meet the criteria detailed above. These methods can additionally be claimed to be more suitable for investigating risks connected to

[9] London Underground (LU) is part of Transport for London, the statutory body for delivering transport in London.

[10] It is a not-for-profit company owned by major industry stakeholders. The company is limited by guarantee and is governed by its members, a board and an advisory committee.

[11] The proprietor and manager of infrastructure for the vast proportion of railway networks within Great Britain. Network Rail is an arm's length public body of the Department for Transport with no shareholders, which reinvests its income in the railways.

turnouts as no elements of railway turnouts are incorporated in the risk management chain(Taig and Hunt, 2012). These techniques can also be expressed to be more inappropriate to the investigation of turnout-associated risk as no part of railway turnouts is included into risk management chain[12]. Moreover, this kind of approaches followed by LU, Network Rail and RSSB has been proved to not be reliable (Taig and Hunt, 2012). In summary the following problems are addressed for a distorted picture of risk:

- The models might be incomplete - omitting possibly important but infrequent events that have not previously been observed in the UK.
- The data upon which the models are founded could be insufficient or imprecise due to deficient recording of incidents and reporting/and or data inputting.
- Differences in different models for various events could render the relative nature of events (hence the priorities obtained from them unreliable.
- The fundamental nature of the models is that they look backwards, in the sense that risk is quantified on the basis of historical incidents instead of forecasting the present underlying risks.

As regards the insufficiency, comprehensive analysis of incident and accidents experienced internationally has been conducted. In cases where this analysis has revealed new incidents, they have been included in the modelling process to generate estimations of frequencies and outcomes that are appropriate for the UK.

As regards the data and model calibration, a particular causal factor of train derailments at turnouts can be defined as an infrequent occurrence. Rather than

[12] As an example: `https://www.rssb.co.uk/safety-risk-model/safety-risk-model/_layouts/15/WopiFrame.aspx?sourcedoc=/safety-risk-model/safety-risk-model/Documents/archive/7.5/RPB%20Table%20A1.xlsx&action=default`

a holistic strategy (where all risks are combined in the analysis). A particular risk group alone should be investigated first, and after this investigation, the impact of this particular group on another one should be examined. This could enable the risk analysis reliability to be improved.

As regards the level of consistency throughout the different factors that contribute to derailment risks, the (revealed) relative contributions to the risk of derailment associated with turnouts from various sources should be examined in a unique model.

As regards the models being backward looking, the existing models do not apply a process of scaling up the incident frequencies in order to take into consideration the differences between current volumes of railway activity and the volumes that were extant over the period to which the safety data used relates. Thus a new easily updatable model is needed.

To establish a suitable strategy and to diminish the frequency of operation downtime, financial impacts and injuries, a thorough comprehension of the risks associated with turnout systems is of paramount importance. The risks posed by turnouts are highly significant and can differ considerably according to the volume of traffic, environmental factors (i.e., extreme seasonal temperature differences, intense precipitation, high wind), the type of turnout system (i.e., standard, diamond, crossover, the position on the track (i.e., yard/siding, main line). If these factors are not suitably considered, it will not be possible to comprehend the behaviour of turnouts via operational span and to determine an appropriate system for managing risks experienced at railway turnouts.

Therefore, it is important that a number of risk management methodologies for railway turnouts are developed, which integrate the processes of assessing, monitoring and managing the different risks and uncertainties linked with them in an appropriate manner. This allows more risk drivers to be applied in an efficient or effective way in a broad range of railway operational conditions.

1.3 Research Gap

A pioneering study that attempted to examine the existing risk associated with turnouts is by Hassankiadeh (2011). He categorised the different types of failure that occur in turnout components and ascertained the most significant types of failure that are observed at turnouts. The study was based on data regarding the failure of turnout components within UK during 2009, and assumed that the characteristics of each turnout were the same by neglecting the factors that differentiate each turnout system, e.g. geographic location, volume of traffic. Therefore, the study seems to be incomplete, utilising a set of primitive techniques only used for risk prioritisation of turnout components.

A further study was performed by Liu, Saat and Barkan (2012).The data used in the development of this study was based on accidents involving freight trains in the United States, categorised by type of track, type of accident and the cause of the incident. Their findings indicated that the primary causes of train derailments on main tracks are track and equipment failures, improper use of switches and violation of switching. Therefore, causes related to human actions were determined to have the same prevalence at turnout systems as the failure of components. Conversely, this study did not categorise the modes of failure, which was recommended for further research.

Various researchers have focused on the risks associated with railway systems that originate from a number of key elements that are additionally incorporated into turnout systems. A key study was conducted (2006) who developed a model to analyse the risk of derailment using a probabilistic approach for rail defects and breaks. Kumar (2006) improves the model through FTA, ETA and FMEA methods. Zhao et. al (2006) applied improvements to established methods of analysing risks by incorporating a fuzzy reason approach with the aim of addressing the uncertainity inherent to the assessment of risk. Nevertheless, this type of probabilistic strategy frequently neglects to take into account the relation between immediate cause, causal factors and contributory factors.

Freitas, Colosimo and Santos (2010) claimed that, among the different approaches used in the railway industry, the Bayesian approach seems to be a more reasonable choice for complicated models, including causal factors and contributory factors. Furthermore, this approach was employed by Mahboob (2013) to model and assess the risks posed to life associated with railway networks via Bayesian networks and influence diagrams. Similarly, his findings revealed that the quantitative assessment of risk and decision support based on risk in relation to railways showed improvements compared with more established modelling approaches (e.g. FTA).

Since studies on derailment causes at turnouts are still new and limited (Hassankiadeh, 2011, Liu et al., 2012), more studies covering various large scale causes altogether are needed to better understand the risk components of turnouts, and to prioritise the risks by investigating their relationship to different types of turnouts in various operational environments.

Over the last ten years, there has been an increased focus on improving risk analysis methods for derailment arising from the many reasons mentioned in the background as they are a provable way of identifying and assessing factors that could negatively affect the success of smooth railway operation(Chen, 2013). Nevertheless, only a minimal number of studies have been conducted to investigate the risk of derailment at turnout systems, and the focus is generally constrained to addressing issues related to the interaction between wheels and rails (Alarcón et al., 2016, Pålsson, 2014).

Although decision-making on the reduction of the risk is quite progressive in the other railway systems such as bogie-set design (Mousavi-Bideleh and Berbyuk, 2016), reater effort is necessary for turnout systems to keep up with them because several basic works have been done and have been inconclusive. A concrete and tangible need for risk modelling through Bayesian analysis for railway turnout systems is seen to not present in the literature. Moreover, the complex nature of turnout systems, involving interdependencies between system variables and uncertainties, is expected to be quite fitting to the use of the Bayesian networks, proven to be one of the best practices for railway in recent studies. In addition, considering the limited number of studies as well as the abundancy of system variables and uncertainties, the fuzzy reasoning approach into Bayesian network analysis is implemented in order to establish a risk management framework for railway turnout systems.

On the other hand, Wang et al. (2017) proposed a bayesian based model which can predict failures of turnout component. However, the proposed model lacks any consequence analysis such as derailment, and is not possible to integrate through national railway network, as the methods relies on small segmentation of railway network.

Table 1.1. summaries the research gap in railway safety researches for turnouts. As can be seen first, there is a limited number of studies dealing with railway turnouts. Moreover, the presented researches cannot be relevant to the scope of thesis, as the derailment causes and their relations between each other on the entire railway network are investigated. Secondly, probabilistic graphical models whose their capabilities are representation, inference, updatability and learning, are rarely used in railway safety researches. Instead, narrow methods, such as FTA, ETA have been used to determine risk. This kind of researches cannot

be updated properly, which means the monitoring of risk (as an objective of the thesis) cannot be performed.

Therefore, this thesis is established to first fill the gap regarding accident studies associated with turnout-related derailments. As seen in Table 1.1., most risk studies in railway engineering have been observed to be related not to turnouts, but plain lane. Secondly, it is understood that the techniques used by all studies are quite primitive as regard to a complex railway infrastructure (see Section 1.2), and cannot be applied for rail turnouts to reach satisfying results regarding any derailment analysis at railway turnouts as the derailments require a comprehensive investigation which concentrates specifically on a few derailment-causes (see Chapter 3 and 4). As a result, novel risk analysis methodologies should be designed particularly for investigating of risk analysis/management. Thirdly, a gap associated with the reasons for the derailments is identified. These novel methodologies are used by the thesis to determine and analyse the risk of the reasons (see Chapter 5 to 7). In conclusion, the identified research gap which has not been answered appropriately (through primitive methodologies) or at all (derailment reasons) in the given field of study will be filled with the chapters above.

Table 1.1: Demonstration of research gap

Research	Description	Gap/Issue
(Zhao et al., 2006)	A track deterioration model and a tamping model were developed	absence of consequence (e.g derailment) analysis, not relevant to railway turnouts
(Kumar, 2006)	Various types of rail degradation and defects processes were studied at particularly turnouts	uses methods, which are challenging and impossible to update (FTA, ETA and FMEA), and focuses on only component failures
(Freitas et al., 2010)	A degradation mechanism was investigated through a bayesian approach	uses methods (FTA, ETA and FMEA), which are challenging or impossible to update results (in other words, absence of monitoring), focuses on only component failures
(Hassankiadeh, 2011)	Turnout component failures	conducted through unreliable basic statistical presentation
(Liu et al., 2012)	Statistical analyses were conducted to examine the effects of accident cause, type of track, and derailment speed.	basic statistical presentation
(Mahboob, 2013)	Bayesian Networks were used to model and assess the life safety risks associated with railways	Railway turnouts were analysed only for signal-pass-at-danger
(Chen, 2013)	A proposal was made to ensure proper maintenance option.	The study uses methods, which are challenging and impossible to update (FTA, ETA and FMEA), focuses on only maintenance strategies
(Pålsson, 2014)	A method is conducted for the optimisation of switch rail profile geometry	This study is limited to a simulation for turnouts exposure to different wheel–rail contact forces. Derailment was not discussed
(Alarcón et al., 2016)	The study presents the power dissipation in a wheel/rail system through friction work modeling.	not relevant to railway turnouts.
(Mousavi-Bideleh and Berbyuk, 2016)	The study investigated optimisation of bogie suspension to boost speed on curves	not relevant to railway turnouts.
(Wang et al., 2017)	The study investigated a failure prediction model based on Bayesian Network to evaluate the effect of weather on railway turnouts	Consequences (derailment) were not discussed. The investigation is limited to a particular area.

1.4 Research Purpose

The purpose of the research work is to develop frameworks capable of modelling risk, risk monitoring and risk management at railway turnouts using a range of engineering approaches for better understanding of existing risk as well as possible increasing risk in the future, and establishing an optimised maintenance strategy.

1.5 Research Objectives

The aim of the PhD thesis is to investigate the significant derailment causes at railway turnouts and to propose a technique to examine the relationship between them. This research deals with three elements: risk analysis, monitoring and management strategies. Thus:

The research objectives for the risk analysis on railway turnout systems are:

- The identification of risk prioritisation of turnouts in various operational environments
- The development of a concise and intuitive visualisation of a framework
- The establishment of relation between two causal groups

The research objectives for monitoring and management are:

- The identification of potential risk changes of turnouts-related derailment drivers in various operational environments

In order to achieve these objectives above, the fundamental objective is:

- The identification of an appropriate risk analysis method to railway turnouts

1.6 Structure of the Thesis

This section describes the main elements of the thesis, and their relations each other. Figure 1.6 clarifies the structure of the thesis and helps the reader find the correct focus for the works. The first section of this chapter examines technical descriptions of turnout systems, the process of risk management, and illustrates the fundamentals of this thesis. The next chapter identifies studies ,which represent the current knowledge including substantive findings, as well as theoretical and methodological contributions to accident analysis in railway industry. As a result, a proper risk analysis technique is identified for the use of the next chapters. In Chapter 3, the statistical data is presented incorporating variables, entities and de-

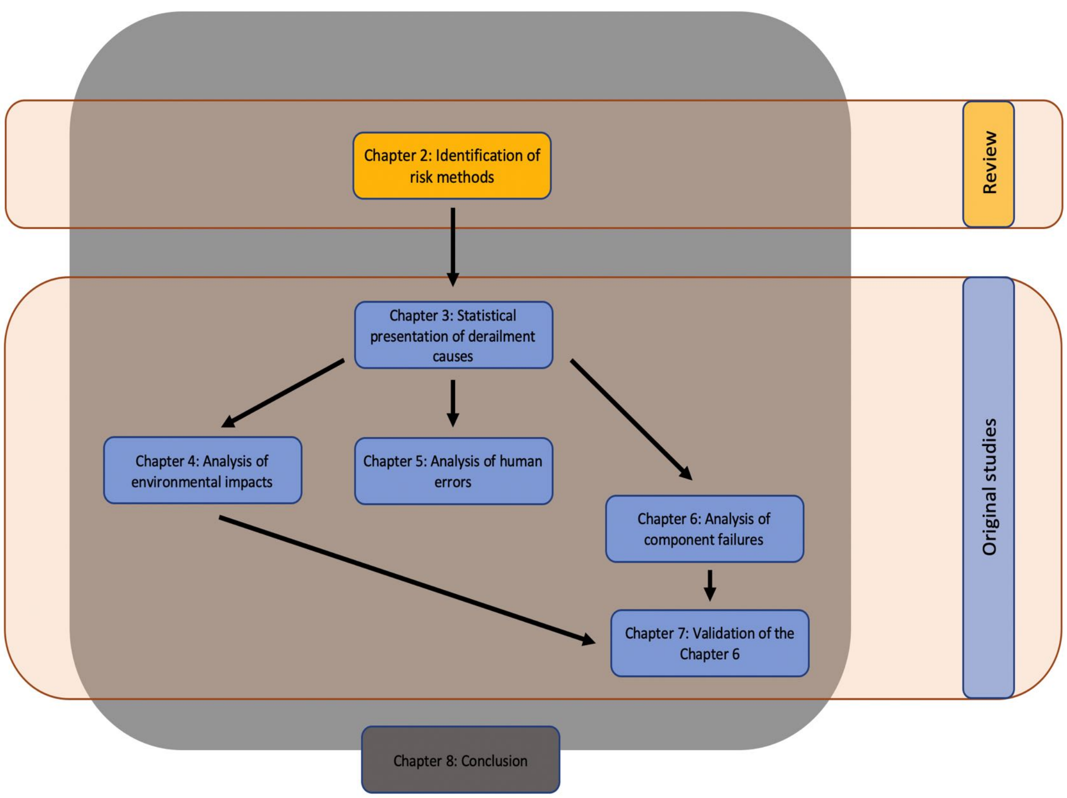

Figure 1.6: Schematic diagram of the thesis structure

railment incidents in order to ascertain the probabilistic or statistical associations quantitatively. Additionally, the causes of derailment are categorised properly. In the light of this categorisation, three primary causes are decided to be included into the scope of the thesis. Subsequently, these causes, namely environmental factors (Chapter 4), human mistakes (Chapter 5) and component failures (Chapter 6) are identified for the purpose of analysing them via the method (Bayesian analysis) determined in Chapter 2. Chapter 6 directly benefits from achievements of two chapters; namely Chapter 3 and Chapter 4. Chapter 7 is a validation study using processes by which the reliabilities of a novel proposed method in Chapter 6 and some methods already available are established. Ultimately, the thesis is concluded by Chapter 8, which includes a summary of the contributions made by Chapters 2 to 7 as well as the implications of the findings for future work.

This doctoral thesis is written in the format of collection of articles (see page vii), commonly called a compilation thesis. The structure of the thesis is based on alternative format thesis guidelines (7.4.1 from University of Birmingham regulations). Table 1.2 shows the specific details of the thesis chapters. These chapters not only depict different techniques, but they also represent novel findings, broadening the horizons of research into risk and uncertainties in relation to safety-critical railway infrastructure. Each of the chapters presents a specific methodology and utilises different data to meet the goals. Two different programming languages – Matlab and R – are used to reach appropriate solutions to each of the novel equations formulated for this thesis. Chapters 6 and 7 used a Metropolis-Hasting algorithm adapted for integration into a stochastic risk model established using R. Via Chapter 7, a novel research hypothesis has been determined and subsequently proven by utilising the previously developed complex and distinctive stochastic risk model, which underlies the considerable computational and scientific innovation that do not exist in the current literature.

Table 1.2: The fundamentals of the Chapters

Chapters	Methodology	Data	Software	Sampling	Objective
Chapter 2	An analysis of risk analysis methods used in railway safety researches, and their advantages and disadvantages.	Provided from the studies in the railway literature	-	-	The identification of an appropriate risk analysis method to railway turnouts.
Chapter 3	Descriptive statistical analysis	Over 100 derailment cases in the UK since 2006	-	-	The identification of risk prioritisation of turnouts in various operational environments.
Chapter 4	Bayesian Network	Over 500 cases in the US during the last ten years. The cases are related to environmental causes.	Matlab	-	(a)The development of a concise and intuitive visualisation of a framework, (b) The development of a concise and intuitive visualisation of a framework, (c) The identification of potential risk changes of turnouts-related derailment drivers in various operational environments.

Table 1.2 *(Continued)*.

Chapters	Methodology	Data	Software	Sampling	Objective
Chapter 5	Bayesian Network	Fuzzy logic based on expert opinions	Matlab	-	(a)The development of a concise and intuitive visualisation of a framework, (b) The development of a concise and intuitive visualisation of a framework, (c) The identification of potential risk changes of turnouts-related derailment drivers in various operational environments.
Chapter 6	Bayesian-based mathematical model	Over 500 cases in the US during the last ten years.	R	Gibbs	(a)The development of a concise and intuitive visualisation of a framework, (b) The development of a concise and intuitive visualisation of a framework, (c) The identification of potential risk changes of turnouts-related derailment drivers in various operational environments.
Chapter 7	Bayesian-based mathematical model	Assumptions on risk indicators and over 500 cases in the US during the last ten years.	R	Gibbs	(a)The development of a concise and intuitive visualisation of a framework, (b) The development of a concise and intuitive visualisation of a framework.

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CHAPTER 2

IDENTIFICATION OF APPROPRIATE RISK ANALYSIS TECHNIQUES FOR RAILWAY TURNOUT SYSTEMS

2.1 Introduction

In Chapter 1.3, gaps in the researchers' knowledge in the field of research of this thesis have been identified. It is observed that, although a number of risk analysis methods have been used, there is only a smattering of information as to why the chosen method is preferred. The thesis is aimed to ascertain risk levels of particular causes, which will be identified in the next chapter. Moreover, the focus of the thesis is on derailments at railway turnouts, which methodologically requires a particular attention, since these kinds of railway accidents are rare events that result in large impacts and are hard to predict.

As there has been no review study that has addressed risk analysis techniques in the context of railway engineering, this chapter concentrates on the identification of appropriate risk analysis methods for railway turnouts. As a result, the novel findings of the chapter will enable the most suitable risk analysis technique to be adopted to the methodologies of Chapters 4 to 7.

2.1.1 Risk and safety

Railway systems have highly complicated geometries, as a significant amount of constituents are interconnected. Derailments largely occur as a result of knowledge deficiencies caused by this level of complexity (Chattopadhyay et al., 2014). One such system is the turnout, which is essentially a mechanical structure that facilitates the transition of flanged vehicles between tracks.

Due to the fact that turnout systems are characterised by their complexity, it is important to focus not only on the component failures that occur in the railway system, but additional failures related to operations (i.e., communication system deficiencies, environmental aspects (e.g., inclement weather) and interaction issues (i.e., searches when identifying the probability of any incident in every railway turnouts). This is because every system has specific technical attributes. Hence, it could be claimed that each turnout has a variety of different kinds of possible causes that could lead to derailments irrespective of the quality of their construction, monitoring and maintenance.

In such situations, the process of risk analysis, an important stage in the management of risk (see Chapter 2.3) is an essential factor in the reduction or potentially the elimination of train derailments in specific instances. A variety of different risk analysis methods have been developed, where each could have benefits in comparison to the others in the context of the railway sector for various reasons. Analysts must select a technique that provides more pragmatic results, otherwise, unwanted outcomes, wasted time and excessive costs will likely occur (Mullai, 2009).

Therefore, in order to fully comprehend the prevailing risks at turnout systems, it is essential that suitable kinds of risk analysis techniques are determined within the railway sector to achieve this objective.

2.1.2 Scope, significance and originality

There is now an increased focus on the risk analysis of railway systems due to the fact that it is not always possible to quantify ambiguities and they particularly cannot be directly associated with susceptible assets and elements, which is dissimilar to mechanisms whose failure modes can be identified (Kaewunruen et al., 2005, Nateghi et al., 2016, Shortridge and Guikema, 2016). The risk and susceptibility resulting from the complicated essence of turnout elements under a variety of different operational conditions has therefore been analysed and initially emphasised within this Chapter. The understanding of the integration and prioritisation of risk can facilitate the enhancement of adaptive practices for maintaining turnout systems. It is possible to integrate the appropriate methodologies within the design and preparation phases with the objective that turnout infrastructure resilience can be incorporated, thus enhancing public safety and reliability (Kaewunruen et al., 2016). Incidents of derailment caused by component flaws could be associated with link wagon-based constituents, like bearing or axle failures resulting from loading issues, or various different constituents of track geometry. Therefore, this Chapter purely concentrates on not only the failure of components, but also all kinds of operational failures, interaction uses, environmental issues and human aspects.

2.2 Risk Analyses

2.2.1 Risk matrix

The risk matrix approach is often semi-quantitative and referred to as preliminary risk analysis. The approach is easy to use and perform properly, provided that the following drawbacks are resolved (Braband, 2011):

- calibration for intended application is required
- the parameters, such as likelihood and frequency, are based on subjective definitions, which could result in comprehending complexities
- the risk results are only reasonable for systems to which the risk matrices can be applied
- in order to properly conduct a risk analysis based on risk matrix, the three steps

Determine the possible consequences, likelihood of occurrence and Risk scoring matrix should be followed (Clinton, 2014).

2.2.2 Failure mode and effect analysis (FMEA)

This is a qualitative method, due to its inductive nature, which aims to identify potential failure modes of the components and to analyse the effects of those failure modes in an engineering system (Recht, 1966, Stamatis, 2003). The system components to analyse individually could be selected according to the degree of disability of system operation or by accidents with significant external consequences. Whilst a single system component is considered at a time, the other components are assumed to work at the same time (Ravi Sankar and Prabhu, 2001, Zio, 2007). As FMEA is asserted as not fit for critical combinations of component failures (Birolini, 2010). The analysis proceeds as follows (Dindar et al., 2017):

- Break down the system into independent subsystems:
  - Identify the various operational modes for each subsystem, e.g. maintenance
  - Determine its configurations when operating in such modes, e.g. a rail-grinder in progress
- Compile a suitable table for each subsystem in each of its operational modes. The table should not neglect any of the subsystem components and include its failure modes and the effects on the subsystem

2.2.3 Reliability block diagram

A reliability block diagram (RBD) is a diagrammatic method performing the system availability and reliability analyses on complex and large systems using block diagrams to show the components (or failure events) and network relations in the system (Birolini, 2010).

2.2.4 Fault tree analysis

Fault tree analysis is a deductive technique, which enables the building of causal relations resulting in a given undesired event. This analysis approach begins with a defined system failure event and reveals backward its causes, down to the primary independent faults (Sadiq et al., 2010). FTA concentrates on a single system failure mode and is able to give qualitative information on how a relevant event may occur and what consequences this event can cause (Thekdi and Lambert, 2012). The steps in fault tree construction are as follows:

- The selection of the system failure event of interest, known as the top event. The following event or events is/are considered with regard to its/their effect on the top event.
- Identification of contributing events, which might directly cause the top event to occur. As such, four possibilities under this step exist:
  - primary failure of the device (e.g. ageing, fatigue)
  - secondary failure of the device (e.g. earthquake)
  - no input to the device
  - human error in actuating or installing the device

2.2.5 Event tree analysis

Event tree analysis (ETA) provides an inductive approach to evaluate the consequences of an initiating event and the likelihood of each of the possible sequences which may occur (Ericson et al., 2015). This approach is constructed using forward logic. The failure, partial failure or success of different systems and subsystems are often represented by the branch points on the tree structure.

2.2.6 Markov analysis

Markov analysis is a stochastic technique that enables the computation of the probability of failure or repair characteristics of individual components in a specific state at a given time (Andrews and Dunnett, 2000). In contrast to simulation-based analysis, this is a well-suited approach for rare events, and, thus, allows such events to be analysed within a reasonable amount of time.

MA is based on the Markov Process, a stochastic process governed by transition probabilities. A Markov Process is characterised by two main concepts: its system and transaction states. The former constitutes the system at any given moment of time, while the latter governs the changes of a state that happen within a system.

2.2.7 Hazard function

It has been seen that Hazard function (failure rate) can be applied satisfactorily in the railway and transportation sectors (Sapoznikov and Anders, 2009). It is a function showing the probability of railway components, system, process or operation failure at time 't' given these are functioning up to time 't'.

2.2.8 Bayesian analysis

The striking difference between Bayesian and frequentist[1] methods is in the definition of probability (Perkins and Wang, 2004). According to a frequentist, probability is considered as a long-run frequency. In other words, it is asserted that the probability of a fair coin toss landing heads up is half of the whole possibility, 0.5, in the long run. Conversely, a Bayesian expresses a belief in the degree that the coin lands heads. This definition of probability is often termed subjective probability. While probability is used by a frequentist to express the frequency of certain types, which happens over repeated trials, a Bayesian, in practice, uses it to

[1]a type of statistical inference that reaches a conclusion from sample data by emphasising the proportion or frequency of the data.

express belief in a statement about unknown quantities (Glickman and Van Dyk, 2007).

In Bayes analysis (BA), when further information is provided, the structure of the model can be updated (Gelman et al., 2013). This feature may be helpful, as the statistical uncertainty is largely present and the amount of available data is sparse. The other advantage of BA is to integrate experimental data with reliability data at all available levels through Bayes' theorem (Graves and Hamada, 2010). The theorem underlies how to update beliefs for prior probabilities.

2.2.9 Monte Carlo simulation

Monte Carlo is a problem-solving technique used to understand the impact of risk and uncertainties by running multiple trial runs, called simulations, using random variables (Couto et al., 2013). The simulations are the process of running a model, aiming to obtain numerical results, numerous times with a random selection from the input distributions for each variable. The outcomes of these numerous scenarios might give a most likely case to approximate the probability of certain outcomes, as well as a statistical distribution to reveal the risk or uncertainty involved (Brooks et al., 2011).

2.3 Discussion

To assess emerging risks in the railway sector, a large number of risk analysis methods, which might be used for a turnout in railway industry, have been evaluated comprehensively in this chapter. This thesis deals with derailment causes arising from a complex nature of a railway infrastructure and cannot be matched by simple multiple-criterion decision-making framework, without the insights into multi-layer asset vulnerabilities derived from expert opinions. Some of them are observed to depend largely on statistical techniques to deal with variables for risk analysing. Additionally, the limitations and expert opinions associated with the risk analysis methods are discussed throughout the chapter.

A railway-related risk analysis is often of scarce, incomplete or, sometimes even has missing data (Rabatel et al., 2009). The weakness in building a satisfying database arises mainly from building new lines, the new materials used in railway tech, and climate and traffic density changes over the years (NetworkRail, 2014). As a result, many precise safety estimates for the ensuing years need to be carried out, as many of the changes mentioned above have already occurred or will.

These changes have been seen to give rise to component failure rates. In the case of complex and sparse data, it is argued that quantitative-based methods, e.g. Monte Carlo (MC) or Hazard Function (HF), should be chosen to provide better information of possible risk factors and their consequences (Billinton and Li, 1993, Marseguerra and Zio, 2002). In contrast to a deterministic approach, the well-built stochastic approaches of MC and HF might allow railway operators to eliminate undesirable time and financial losses. In contrast to a deterministic approach, the well-built stochastic approaches of MC and HF might allow railway operators to eliminate undesirable time and financial losses. This is because the probabilistic component failure models of the MC and HF techniques are entirely appropriate to complex engineering systems such as a turnout.

Furthermore, a recent study (Parks and Rogers, 2008) has illustrated that such methods have another advantage over others for any type of infrastructure, particularly large-scale systems, man-made, networked and operated from long distance, since their results provide much more solid information on total system vulnerability as a function of the input variables.

Considering the above papers and their conclusions, their methods could be well-adapted into any risk analysis attempt at understanding to what degree each component of a turnout system could have an effect on the safe passage of wagons through the turnout. This kind of research should be directed at optimising the maintenance intervals of system components in a particular type of the turnout. Considering how different is each response to safety failures, consequently contributing to the overall system vulnerability of the turnout, stochastic modelling using one of the two approaches is likely to suit.

However, the core problem of object-oriented modelling for complex engineering systems is related to slow simulation speed and the large number of input parameters (Eusgeld et al., 2009). Additionally, this thesis prescribes that the subsystems of a turnout should be taken into specific account in the railway industry risk management chain. Instead, the industry currently prefers to accept the system as whole or simply classify it as railway turnout. From this perspective, these kinds of classifications make the investigation of risks vulnerable and inadequate. They need to evolve to approach sound estimates. Such an evolution would be able to take measures against risk and vulnerabilities due to a better understanding of how these arise in the complexity of turnout systems (RSSB, 2009).

The importance of ensuring how accurate and appropriate data are collected is vital. Given the subsystem levels of a railway turnout as the aim of the risk assessment study, it is expected to have two possible sources of data, which might be used for the assessment: (1) data through the analysis of similar railway systems, such as crossings, and then allocation/contribution of failures to the subsystems of a turnout, and (2) data through elements and components of the subsystems of a turnout (Nejad and Mathias, 2013). The latter is known as the bottom-up approach, while the former is the top-down approach. It is significant to underline that this classification is based, not on the organisation of the data, but the source of the data.

A failure to display signals at a turnout is a good example as the top-event probability in a fault tree model. If any turnout subsystem related to signalling process leads to a failure, then it should be considered a bottom-up approach. On the other hand, if a failure to display signals is based on observation, e.g. the identification of procedural faults, and if the basic event probabilities, e.g. human-oriented operational failure of signalling, are the sole allocation of top-event probability based on various criteria, then the same FT model would be considered a top-down approach.

The results of these two approaches are highly likely to vary. Effort in deciding the structure of the study could be unrealistic. ASA's recent study of a complex engineering system (Nejad and Mathias, 2013) revealed that a sound estimation might be achieved with the application of both to a study, and then the aggregate of the study outcomes and overall failure probability can be reached using techniques such as Monte Carlo.

Expert review is still one of the most essential elements in understanding risk components in railway studies (Park et al., 2008). In the literature, it is noticed that over 500 railway review-based risk analysis or management articles, reports and conference proceedings appear to have been published since 2010.

The implementation of expert review into risk analysis is often quite difficult, or even impossible in some cases (Schmucker, 1983), e.g. hazard function. On the contrary, more simple methods, such as FMEA, FTA or risk matrix could be more suitable to review implementation (Nedeljaková, 2007). Furthermore, the majority of these methods are generally designed with a top-down approach. It is also important to choose methods for eliciting and aggregating expert opinion. The elicitation and aggregation processes of expert assessments are classified into two groups: behavioural and mathematical approaches (Clemen and Winkler, 1999). The former aims to produce some type of group consensus among experts, while the latter is performed by the decision-maker using a set of mathematical methods.

In 2004, a research study based on the review implications provided solid information as to what aggregation techniques are effective in satisfying outcomes, by investigating 90 studies in different fields (Ouchi, 2004). However, the results show that there seems to be no prominent all-purpose aggregation method for expert opinion, even if mathematical methods of aggregation, e.g. Bayes, often yield better results than behavioural methods. Additionally, expert review is one of the most essential elements in understanding risk components.

One of the suitable methods for expert reviews, risk matrix is one of the common methods for risk assessment and risk classification in the railway domain, e.g. BS EN 50126-1:1999; BS EN 50126-2, 2007; BS ISO/IEC 26702, 2007. However, the technique has some concerns regarding (Anthony , Tony, Baah et al., 2015, Korombel and Tworek, 2011);

- calibration to their particular application

- the dependence of results on the system level to which it is applied
- vulnerability on the determination of parameter classes
- challenges of directly taking barriers or risk reduction factors into account in the risk matrix

On the other hand, the risk matrix is a well-accepted and easy-to-use tool, and can be useful for risk prioritisation, allowing these problems to be eliminated (Alexander and Marshall, 2006, Duijm, 2015). The elimination can be made through combination with another method, which could additionally take into account the effect of barriers and their related risk reduction (Braband, 2011, Zhao et al., 2009). One of the most prominent candidates for combination is FTA, as used by risk priority numbers in the railway domain. Indeed, risk matrix has lost its reliability because accessible and improved large railway databases enable the performing of well-built sensitive quantitative analysis. A study of train control systems has been conducted for a comparison of risk matrix with a set of risk analysis methods, including semi quantitative (upgraded risk matrix methods) and quantitative (Jo et al., 2007). Although the results of a basic risk matrix are seen to be unrealistic in regards to safety estimation, a proposed semi-quantitative method alongside the use of risk matrix is determined as the best approach. However, the research might be considered as incomplete and open to criticism, considering it does not include FTA-based or any advanced qualitative techniques, e.g. Bayes, in comparison. In the case of such a comparison, the chapter is highly likely to have given a different conclusion.

Figure 2.1 shows the overall approach, jointly with additional and alternative steps. As seen in the Figure, when barriers cannot adequately be evaluated by score tables, FTA can be added into the chain to determine what is needed,

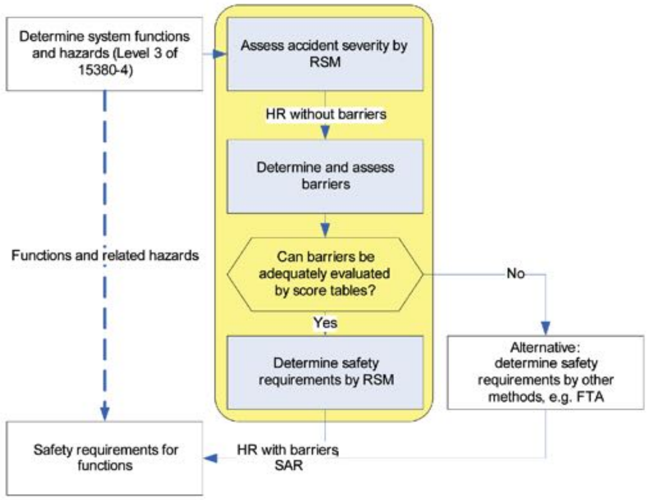

Figure 2.1: Overview of the combination model

e.g. safety requirement in this case. Therefore, the final output comprises the assumptions on which the analysis rests, which may result in SAR (safety-related application rules) and HR (hazard rates) related to the functional failures (as hazards) of the technical system.

Some methods take proactively preventative measures, whereas others, e.g. ETA, do not. For instance, the focus of FTA is on provision against multiple causes leading to a number of undesired events. In other words, the events are likely to occur in the future and the probability of their occurrences is assumed to be reduced through FTA. On the other hand, the focus of ETA could be on mitigation measures leading to multiple consequences after any event occurs. Hence, the use of failure tracing methods is widely different from one to the other, since actions are taken either actively or proactively.

In fact, the two are complementary and are generally used together by focusing on opposite sides of an undesired event (Figure 2.2).

Figure 2.2 shows how they fit together. This is often called the bow-tie technique. Only a single 'undesired event' is shown in Figure 2.2; in reality, multiple

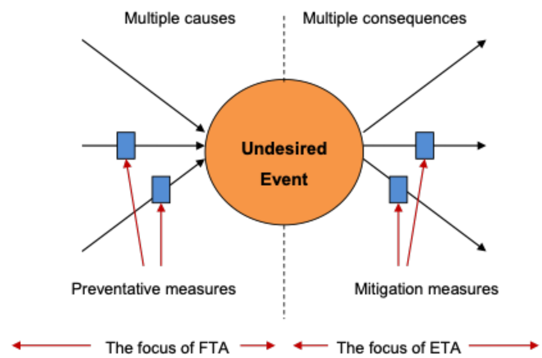

Figure 2.2: Bow tie technique

causes are highly likely to result in many different events, initially, each then escalating with multiple consequences. Each event can be analysed through FTA and ETA. In a nutshell, ETA is interested in stopping an event escalating, whereas FTA is concerned with analysing faults which could lead to it happening. Both can be applied qualitatively or, if data are enough large, quantitatively.

The bow-tie could be used successfully to access the adequacy of controls and identify areas for risk reduction in properly operating railway turnouts. The aim could be to test the robustness and number of existing safeguards and identify improvements. For instance, the technique might be useful for risk assessment of driver-to-signaller train radio communication system failures which are responsible for derailments at the turnouts, as stated in the second section. It inherently has a graphical representation, which might result in easy understanding of the relationships between the causes of unwanted events and their control. The assessment is highly likely to identify procedural controls, along with integrity and functional requirements, and establish issues requiring information, assessment or action where the effectiveness of a control might be questioned.

However, the bow-tie might not be the panacea for all risk management problems. If a particular level of risk is required to be revealed in absolute terms, the technique might not help directly. Similarly, there could be better ways than using bow-ties to model the complex interrelationship between risk controls.

Additionally, there is another issue for classical risk analysis methods, e.g. FTA and ETA, typically decomposing a system into subsystems and basic elements. Investigating risks for a turnout system with strong interdependencies in nature has to go beyond the convention cause–consequence analysis in order to concentrate on spill-over clusters of failures. Indeed, the sum of the behaviour of individual components in a turnout cannot be expected to describe implicitly the behaviour of the whole system. This renders questionable the suitability of such risk analysis techniques. Moreover, pre-defined causal chains, e.g. defined by ETA, are likely to be inappropriate to identify hidden risks.

It is ultimately worth noting that each technique might provide different parameters or outputs that may be particularly useful regarding intended solutions of the problem. Therefore, a risk analysis method should be chosen, not only based on hazard, but also the consideration of the capabilities of each technique.

As a summary of outputs, desired outputs can be simple lists of individual failures (FMEA, RM), numerical estimates of system failure probabilities (MA, RBD, FTA), listings of event scenarios and their likelihoods (ETA), numerical system failure probabilities and sensitivities to input variables (BA, MC), or unique combinations resulting from a combination of these methods (e.g. use of both FTA and ETA).

Using a good example of bow-tie techniques, London Underground Board and the UK national railway network currently rely on their own risk models, namely the LUQRA (London Underground Quantitative Risk Assessment) and the RSSB SRM (Safety Risk Model), respectively. The general common purposes of the models are, briefiy, assessment of risk and risks of change, understanding current risks, identification of mitigation measures and key risk contributors and risk-based improvement planning (LU, 2009, Stamatelatos et al., 2011). The main difference between the two is that the LUQRA is designed by considering more serious injury and fatality relative to minor injuries, due to potential accident consequences in London underground.

In contrast to using the same structured model with bow-tie techniques, their judgements are different to each other. For instance, both the RSSB and the LU use separate fault/event tree models for derailment at various different speeds. Other situations affecting the results, e.g. how far the derailed train moves away from the centre of the track or how many people there are on the derailed train, are considered through the ETA model, which means there are many approximations and assumptions made by different analysts in terms of the points of detail which are less or more important for accident consequences (Taig and Hunt, 2012).

Additionally the LUQRA quantifies first at the system and then at line-level, considering line-specific factors, and, lastly, aggregates the line representations of risk to the overall system representation, whereas the other begins with the whole system representation and then disaggregates it to reach risk representations for individual routes.

The models take into account: train accidents, including collusion and derailment, movement accidents, including various interfacing problems, and other malicious non-movement accidents. However, the RSSB SRM does not inherently include accidents most seen in underground lines, such as flooding and arching, whereas the LUQRA does.

Furthermore, the data used by the both models are: (1) derived from historic data; (2) normalised per relevant unit of railway activity; (3) evaluated to make a decision on whether changes in the railway or its operation may have infiuenced the normalised rate of occurrence of such events; and (4) multiple backups of current relevant volumes concerning railway activity to achieve the best estimation of forecasting the frequency of such an event today. However, in the RSSB SRM, database updates are carried out more often and its database covers a shorter time period.

Upon the request of the Office of Rail Regulation in the UK, a report (Taig and Hunt, 2012) has been published to reveal the one closest to reality through comparison of the general nature of the outputs, produced by both models, using recent actual safety performance. The outputs of the models in the report cover: (1) top event frequencies and annual risks, (2) probability/consequence of top event outcomes, (3) frequencies/number curves.

Comparison between the actual experience of recent years and the current risk model predictions shows that the LU QRA‘s average estimates for five years from 2006–2007 to 2010–2011 are somewhat higher than the reality. The LU QRA predicts about an average six passenger fatalities per year for the events, while the RSSB SRM estimates an average of around 11. However, the actual average numbers per year for the LU QRA and the RSSB SRM are 0.8 for LU and 6.8 for National Rail, respectively. This pessimistic attribute of the LU QRA can be explained by: (1) risk models of included top events not having been updated for some time; (2) the statistical data applied in quantifying the model being derived from longer time periods than tend to be used by RSSB; (3) beginning with a picture of the whole system and then disaggregating it, which could be somehow more beneficial for complex scenarios.

On the other hand, both models provide a distorted picture of risk, mainly arising from the following concerns: (1) incompleteness – leaving out rare but significant events previously experienced in the UK; (2) limited database – using only own database; (3) backward looking – addressing only past events rather than predicting and integrating current underlying risk; (4) uncalibrated process – leading to underestimating or consistently over-estimating safety risks.

To address these in turn: where the models might be incomplete and limited, global events can be incorporated into their database with proper modelling to obtain appropriate estimates of frequencies and consequences. As regards backward looking, the models make an assessment of risk, doing a scale up/down of current incident rates through multiplication of current activity volumes with recent normalised rates. Although RSSB might occasionally make changes to the recently observed rate, both may need to identify the sensitivity of risk to various aspects of safety performance improvement in accordance with their activities.

With regards to the data calibration of the models, the LU might err on the side of pessimism in its risk estimates, as smaller units of railway increase the areas where the model could tend towards using longer term incident data.

All the methods to use in a railway turnout system are evaluated in the following Table 2.1 (Marhavilas et al., 2011, Rasche, 2001, Skorupka, 2008, Stamatelatos, 2000)

In summary, railway turnouts are complicated systems that are utilised to deviate trains between tracks. The geometry and gradient limitations render them critical components of railway systems. The significantly complex nature of railway turnouts has resulted in emerging risks in railway operations. This fact has been demonstrated by the large volume of derailed trains on or close to turnouts. There appear to have been around 500 derailments per year in the last ten years, of which 7% (35 derailments) involved catastrophic consequences (Robinson et al., 2012). These accidents often lead to operational interruptions as well as financial costs, and occasionally even deaths. Hence, it is important

Table 2.1: Comparative evaluations of risk analysis methods in railway industry.

Methods	Life cycle phases	Strengths	Weakness	Availability prediction	Common cause failures	Effect of uncertainty in data	Proactive use
RM	All phases	Quick preparation; suitable in the case of subjective data, e.g. expert opinion on only ties degradation of a turnout	Inadequate for complex systems; cannot identify dependencies such as signalling errors vs. environmental effects	Yes	No	No	Yes
FMEA	After design is finalised	Good for identifying single point failures, e.g. electrification process of a switch mechanism	Human error cannot be addressed; unable to reflect system redundancies, interactions, and Common Cause Failures	No	No	No	Yes
ETA	All phases	Excellent tool to model temporal escalation of events such as high speed-based derailment; ideally suited to model efficiency of safety critical tasks and emergency	High dependencies on the correct capture of event escalation; needs scarce data for such complex systems as ageing any railway components through FTA	No	Yes	Yes	Yes

Table 2.1 *(Continued)*.

Methods	Life cycle phases	Strengths	Weakness	Availability prediction	Common cause failures	Effect of uncertainty in data	Proactive use
MA	After design is finalised	Good for complex systems; good tool for identifying process inefficiencies	Unable to reflect redundancies and Common cause failures	Yes	No	Yes	No
HF	Design of emergency Preparedness plans and evaluation of safety critical tasks	Evaluates existing safeguards and identifies ultimate consequences; May be a good tool to derive safety-based maintenance model of a turnout	For a human-based failures, Quantification may be misleading since such failures are quite difficult to model; due to its reliance on scarce date to model, gathering of data might be difficult	Yes	No	Yes	Yes
MC	To establish properly reliability of system, ideally during consolidated design, but could be used in all phases	Once model built, input distributions are quickly updated to yield new results; an Intuitive process, helping users to add some qualitative data into a mathematical model, which describes the risk parameter; provides a range of consequences, enabling better estimation of risk	Creation of a mathematical model can be challenging; relies on computerised methods, e.g. spread sheeting; satisfaction of the analysis highly depending on complexity	Depends on model	Depends on model	Yes	Yes

Table 2.1 *(Continued).*

Methods	Life cycle phases	Strengths	Weakness	Availability prediction	Common cause failures	Effect of uncertainty in data	Proactive use
FTA	Throughout all stages of operation	May be excellent for complex systems where interaction and combination of events and failure needs to be considered; uses properly statistical data of component failures of a turnout to evaluate probability for unwanted top event; provides visual model of a safety system; provides ranked lists of critical turnout components; an excellent tool based on a qualitative or quantitative application to model redundancies and fault tolerance (vulnerability).	In spite of Databases unsuitable for specific application, e.g. Aging of rail track, failure information might be supported using FORM methods; unable to model temporal events of a turnout such as changing weather conditions. Dependencies on correct capture of faults and failure mechanisms and interaction to predict system behavior.	Yes	Yes	Yes	Yes

Table 2.1 *(Continued)*.

Methods	Life cycle phases	Strengths	Weakness	Availability prediction	Common cause failures	Effect of uncertainty in data	Proactive use
BA	Especially, well-known relationship of failures	Provides a solid decision theoretical framework, forming a prior distribution for future analysis; useful method for fuzzy integration; easily adoptable after new data; shows relationship of nodes	requires time and skill to prepare a solid network	Yes	Yes	No	Depends on model

that railway management organisations approximately quantify the risk profiles presented by railway turnout systems so that the whole railway network can be operated while interconnecting with external modes of transport with no risk to safety.

The Chapter has critically reviewed the current literature, which might relate to derailments at turnouts, and has presented a comprehensive analysis of the methods and applications of risk analysis and modelling. Additionally, The chapter has identified significant knowledge deficiencies related to the sector. It has been observed that the sector utilises a variety of different risk analysis and modelling techniques and produces diverse results, thus causing disparate and inconclusive maintenance implementations. Studies have demonstrated that the railway sector must particularly focus on monitoring and managing interrelated risks so as to enhance public safety and operational dependability. Therefore, this Chapter discusses modern techniques of management incorporating the systems thinking approach, a variety of developing risks and the diverse risk analysis methods. A summary has been provided on the practical guidelines for railway stakeholders with the intention that the processes of managing risk can be further developed with a particular focus on railway turnouts.

It is undeniable that analysing, modelling and management of railway systems offers an indispensable instrument for railway firms and authorities to predict certain situations and then reduce the resulting impacts. Dealing with topics emerging from the discussions, the below points can be emphasised for the purposes of further investigation:

- The advantages of the enhanced flexibility to choose, analyse and discuss pertinent factors of risk analysis modelling to satisfy appropriate safety criteria for railway turnout systems (e.g., the use of an ongoing updating procedure in which a vast amount of outputs are acquired in every specific case by utilising diverse techniques and inputs, and subsequently making a comparison between the outputs and the real situation on an annual basis in order to calibrate the expectations). This aspect will affect all methods devised in this thesis. Hence, only techniques that can be updated will be utilised for the identification, management and monitoring of specific risk factors. To achieve one of the thesis objective for monitoring[2], the thesis adopt Bayesian analysis, which is updatable in accordance with changing risk environment.

- The reaction between more integrated environments for distinct analysis of risk; the different degrees of the variety of risk factors, e.g. aging railway constituents and environmental factors, can be combined to predict the probability of derailment incidents at turnout systems with greater precision, thus identifying the quantitative relationship that exists between them. In this case, the combination of both factors could generate distinctive levels of risk, even within the same stretch of railway, which could potentially enhance the comprehension of the actual degree of risk instead of smoothing out the general risk. This aspect will be reviewed in Chapter 6, which focuses on the concealed effects of weather on constituent failures. The remainder will be presented in Section 8.3 of this thesis, which will make recommendations for future study.

- This thesis is not limited to a region (e.g a specific climate zone) or (a country e.g the UK). This proposed methodologies from Chapter 4 onwards are novel and adoptable to any countries. To ensure applicability of method-

[2] The identification of potential **risk changes** of turnout-related derailment derivers in various operation environments.

ologies, it is necessary to constructing effective database, in which all new incidents that are found are anticipated to happen. Where more effective database to integrate into these novel methodologies is available, the data provider has been changed. To fulfill all objectives, data are not only collected from the United Kingdom (see Chapter 3), but also the United States (see Chapter 4, 6, and 7) as well as Turkey (see Chapter 5).

- Where data is scarce in a particular case e.g relation between derailment causes, the thesis largely has a preference for stochastic techniques. Chapters 6 and 7 attempt to reveal mathematically a relation regarding environmental factors and component failures. A novel GIBBS sampler, a variant of Markov chain Monte Carlo (MCMC) algorithm, is integrated to make database more reliable. The Bayesian analysis is quite suitable to such integration, as Bayesian characterization of errors associated with data limitations is common practice in literature. This fundamentally contributes to one research objective about management [3]

- The impact of similar in-depth Mapping Top Events of estimations in all areas of the sector. In other words, a particular hazard on one side can sometimes be separated into multiple categories on the other. This emerging topic is only included here to present an indication for deterministic-based studies or updatable Bayesian networks to form a suitable methodology.

[3] Development of a novel integrated model for managerial decision on the basis of risk analysis and monitoring objectives.

2.4 Conclusion

This chapter identifies studies which represent the current knowledge, including substantive findings, as well as theoretical and methodological contributions to accident analysis in the railway industry. It is observed that there is no explicit knowledge as to what risk analysis method is suitable to railway turnouts. Therefore, the chapter examines a wide range of studies illustrating their influence on complex infrastructures. As a result, Bayesian analysis is found to enable the thesis objectives to be answered properly. This is identified mainly as applying sampling technique (for scarce data environment) and updatability (allowing for monitoring the risk). This risk analysis method will be adopted in Chapter 4, Chapter 5, Chapter 6 and Chapter 7.

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CHAPTER 3

ASSESSMENT OF TURNOUT-RELATED DERAILMENTS BY VARIOUS CAUSES

3.1 Introduction

The preceding chapter has been designed to examine recent developments in the analysis of accidents connected with railway networks. The existing knowledge surrounding this subject has also been discussed to comprehend the types of risk analysis techniques that are suitable for responding to the research aim, which has additionally been detailed in Chapter 2. Due to the essence of the analysis, logical arguments in regard to the procedure of determining and examining possible derailment causes need to be uncovered. Based on the new research field on which this thesis is focused, it will concentrate on identifying and evaluating the series of incidents that could threaten the successful functionality of railway network management and cause train derailments at railway turnout systems. In other words, one of the risk analysis related-research objective[1] is achieved through the Chapter 3.

Trains could derail as a result of a variety of causes, such as operational deficiencies, environmental effects, collisions, certain mechanical defects, or combinations of them (See Chapter 1.1.3). Consequently, any actions taken to mitigate the possibility of derailments necessitates extensive understanding of the subject. Recently, many rsearchers have performed various studies on the statistical evaluation of derailed trains. Firstly, Liu et al. Liu et al. (2011) assessed incidents of train derailment based on the causes of the accidents. The outcome of this study was a model that assessed the risk of derailment on the basis of the cause of the accident and FRA track category. The same researchers Liu et al. (2012) then showed the statistical findings of serious derailment incidents and their impact on accident frequencies. Nevertheless, the study only focused on safety related to

[1] The identification of risk prioritisation of turnouts in various operational environment

freight trains, omitting other kinds of railway vehicles like passenger carriages and trams. It is important to note that no major conclusions were drawn in regard to the association between causes and derailments related to turnouts.

Conversely, it has been shown that the efficient and maintainable management of risk at railway turnouts could be accomplished through a separate examination of all railway systems (Dindar et al., 2018). Consequently, as turnouts are considered to be railway system with the highest level of complexity, it is important to focus on turnouts on the basis of various different factors, including the kind of equipment, track, instant cause, the causal and contributory factors to the investigated accidents.

Overall, derailments associated with turnouts are responsible for almost 50 percent of all derailment incidents in the United Kingdom (Ishak et al., 2016). The comprehension of the different causal factors that lead to turnout-related derailments can make a valuable contribution to strategies aimed at the prevention of these incidents in addition to the development of economical maintenance actions. This can also reduce the risks associated with railway transportation, enabling railway companies to maintain problem-free networks.

This chapter presents the statistical findings of turnout-related derailments, and subsequently analyses and discusses the findings to accomplish the first stage in a methodical procedure involving the risk analysis, monitoring and management of risk for operational scenarios (Chapter 4 to 7).

3.2 Method

In order for the research to be generalisable and to identify particular levels of risk at railway turnout systems, it is important to discuss the reliability, sufficiency and accuracy of the data utilised as well as the extent to which the data facilitates the understanding of safety within the railway sector. The following section will respond to these concerns.

3.2.1 Data source

This chapter is constrained to investigating causes of accidents in the context of UK railways. Hence, various different UK sources are included in the analyses, one of which is the Railway Accident Investigation Branch (RAIB), which is a UK governmental agency that performs investigations into different kinds of train-related accidents that occur within the UK. Established in 2005, the agency is officially authorised to conduct inquiries into accidents that result in fatalities, severe injuries or significant damage to railway infrastructures. In particular, it concentrates on events and accidents on mainline railways, metro systems, tramways and historical railways across the UK, functioning as an independent organisation.

Comprising a total of 43 individuals, the inspection team consists of highly experienced professionals with knowledge of railways and investigation. The reports they publish on accidents are formally trustworthy and are supervised by the Secretary of State for Transport. These reports produced by the RAIB incorporate the following:

- The immediate cause, causal and contributory factors underling incidents and accidents that occur on railway networks

- The identification of risks that could lead to analogous accidents or worsen other accidents, with accompanying suggestions aimed at preventing further incidents

- In-depth data regarding how accidents on railways

The body has investigated all categories of accidents that have occurred on turnouts within the UK since 2006.

It is worth noting that some chapters will utilise data from overseas (the US and Turkey). The reason why different databases are used is, fundamentally, that the UK rail network does not properly meet the thesis objectives. For instance, component failures are investigated considering climate changes through the rail network. The UK climate regime does not vary and is not comparable to that of the US or Turkey in this regard. Therefore, the other databases are fundamentally considered where the UK database lacks concrete information. Further detailed explanations will be given through the method sections of the chapters.

3.2.2 Data categorisation

The reports prepared by the Railway Accident Investigation Branch are based on a broad range of safety incidents, such as accidents and near collisions, and the scope goes beyond the requirements of the Railway Group Standard GO/RT3119 and Accident and Incident Investigation Guidance, which are primarily focused on operations (RSSB, 2014). Data shows that more than 130 reports on derailment in relation to incidents that have occurred on heavy, light, metro and historical lines have been published by the RAIB. Furthermore, in these reports, a total of 45 incidents were categorised as accidents occurring at turnouts. Additionally, the reports have been analysed to ascertain whether these accidents surpassed a monetary threshold of damage to railway infrastructure and vehicles.

A technique has been established that enables the categorisation of immediate, causal, contributory and fundamental factors related to accidents (Marshall and Healey, 2008). It can be seen that both the RAIB and RSSB predominantly function on the basis of a model and an analogous methodology, which is altered to consider particular problems associated with turnouts based on technical rail categorisation, is utilised in this chapter. The categorisation is illustrated in Figure 3.1. The primary differentiating factor that separates the altered model and the model presently being used is that the updated model incorporates the division of component failures in terms of whether they are related to infrastructure or not, such as bogie faults, wheel flaws, among others. As it has been observed that numerous dearilments are attributed to human errors, these kinds of failure were addressed as main causes.

In summary, all main classifications, namely operational defects, environmental effects, interaction issues and human errors, are provided in Table 3.1 in addition to the sub-classifications. This chapter also endeavours to classify types of railway, such as heavy, light, metro and historical tracks. Additionally, the places in which accidents occur, like rail yards, sidings, or main line tracks, are also considered. This may be beneficial for ascertaining the extent to which the level of risk changes in line with the attributes of the location.

Table 3.1: Subcategories of all major accident nodes.

Infrastructure	Interaction	Environmental	Operational	Loading	Human
Switch	Obstruction	Rain	Signal	Malicious	Speed
Points	W/R	Snow	Use of switch		Breaking rules
Stretcher bar	Flange climb	Mud	Brake operation		Fatigue
Geometry	Hunting	Wind	Train handling		Vandalism
Ballast					

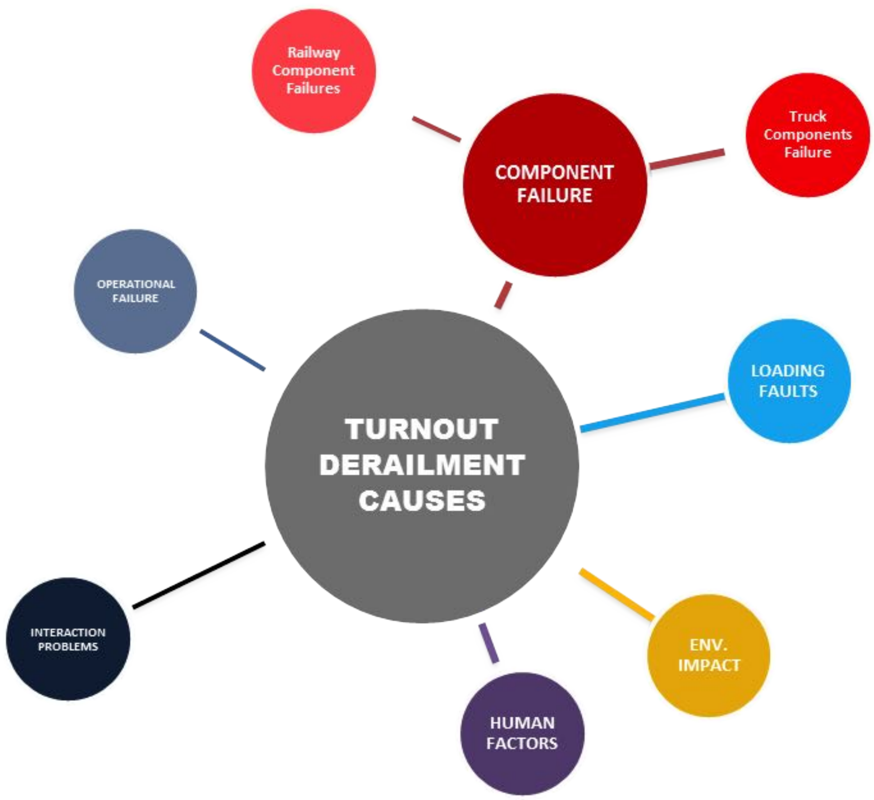

Figure 3.1: Representation of proposed framework for categorisation.

3.3 Results

3.3.1 Derailments by operational type

Four types of railway types are recorded in the RAIB reports, namely heavy, light, metro and heritage rails. Different operational functions might be executed through these different railway types and, consequently, are expected to lead to different causes, accident types and consequences.

Heavy rail refers to conventional railways forming part of the national network, including high-speed rail, freight, intercity, commuter and rural services. RAIB and RSSB use light rail as a term to express high capacity lines on which urban public transport, using rolling stocks similar to a tramway, are used. Metro might be seen as underground light rail, but cannot be accessed by pedestrians or other vehicles of any sort. As for heritage rails, the means that volunteers or non-profit organisations take over or re-open railway lines, which were once run as commercial railways.

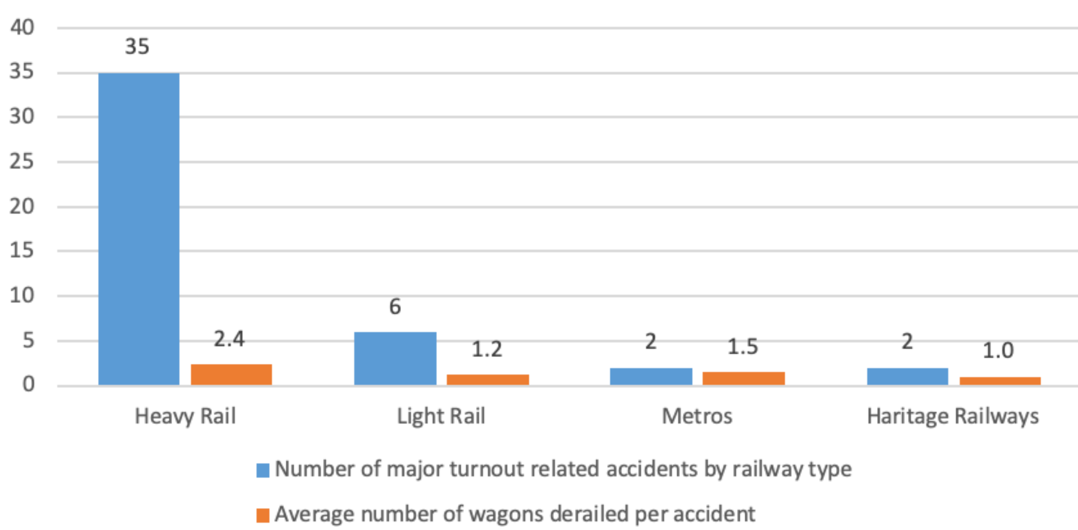

Figure 3.2: The accidental characteristics of turnouts by railway type

Figure 3.2 shows accident frequency and wagon derailment by railway type, considering all reported cases in the UK from 2006 to 2016. It provides evidence that the distribution of accident types varied in accordance with railway type. Train derailment on heavy lines is seen to dominate the overall accidents. Over the last ten years, 35 significant derailment cases, accounting for 77% of all, have occurred on such lines. The most common railway type, it is found to be followed by light rail, metro and heritage railways.

Risk comprises two fundamentals; likelihood and consequences/severity. As the report does not include cost of accidents, e.g. track or rolling stock maintenance expenditure, it is assumed that accident severity is determined by the number of wagons derailed per accident. Similarly, train derailments on heavy lines, an average number of 2.4 per accidents, have had a greater average accident severity than other railway types, namely metro, light rail, and heritage rail, at 1.5, 1.2., 1, respectively.

3.3.2 Derailments by track classification

Three types of track classification are recorded in the RAIB database, namely main, siding, yard and industry line. As with track classification, these are necessary for achieving different operational functions and, as a result, have different associated accident causes and consequences. The chapter uses main line refering to a stretch of railway track that is away from yards and sidings. Yards are a complex series of railway tracks used for loading/unloading, sorting or storing railway trucks, while sidings. There are some lines that are not for public transportation, but for serving a particular industrial, logistic or military purpose. These lines are addressed as industry lines.

RAIB turnout-related accident reports covering the period 2006 to 2016 were

Table 3.2: Statistical results by track classification.

	Main	Yard	Siding	Industry
Number of turnout related accidents by track classification	28	10	7	1
Average number of wagons derailed per accident	2.4	1.6	1.5	2.0
Average speed of derailed vehicles (mph)	14.9	10.5	5.6	N/A

compiled to illustrate the number of major accidents by track classification, the average number of wagons derailed per accident and average speed of derailed vehicles (Table 3.2). It is worth noting that accidents resulted by track classifications include both passenger and freight trains.

These three statistical categories were dominated by accidents on main lines, as expected due to their high traffic density. On the other hand, although yards are equipped with small pneumatic, hydraulic or spring-driven braking retarders to slow train speed, given the British speed regulations, and that these are very common railway areas, there seems to be a relatively greater number of turnout-related accidents than expected. This will be discussed later. However, as only one accident has so far been recorded, it is quite difficult to make any conclusion on the line.

Although serious accidents are seen likely to occur on the yards and siding areas of a railway line, main line operation needs to be considered carefully to maintain a smooth operation of the entire railway network, because heavy trains on this part travel at high frequency and higher speed. The Table 3.2 also illustrates the explicit relationship between speed and number of accidents/average number of wagons derailed per accident. The higher the speed at which the rolling stock travels, the more accidents are highly likely to occur. It could be considered that the rolling stock on main lines are of greater mass than those on other lines. The greater mass and speed signifies that the rail-wheel interaction forces and potential impact with regard to casualties, property and environmental damage, are expected to be all correspondingly greater. This could be an explanation in the logarithmic rise in the number of derailed wagons against rolling stock speed.

3.3.3 Derailments by accidental cause

Derailments are the most common type of train accident type in the United Kingdom. The railway industry and government-based organisations concentrate on preventing them to provide a high standard of railway operation and eliminate potential safety concerns. Several researches have focused on train derailment and causes, using often the Federal Railroad Administration (FRA) database. The administration reports a large number of accidents covering almost the last three decades in the United States, and these reports, each of which is of one or two pages, are as detailed as RAIB reports. On the other hand, the U.S. has a length of nearly 150,000 miles and over 1.2 billion tonne miles of freight rail usage, which is remarkably higher than those in the UK (about 20,000 miles, 23 tonne miles of freight rail usage, respectively)(DfT, 2015). Considering the relation between the numbers above and accidents, it is seen that the study deals with a considerable low number of accidents (rare events). On the other hand, immediate causes, causal factors and contributory factors of these accidents are observed to be explained in detail throughout official reports.[2]. The contributory factors and causal factors have rarely been included in FRA reports.

Most previous studies have concentrated on main line, yard and sidings derail-

[2]As an example: https://assets.publishing.service.gov.uk/media/5bf28782e5274a2aeeae93bb/R192018_181119_Waterloo.pdf

ments; however, this chapter only focuses on turnout-related derailments which demands for elaborated explanation on how a rolling stock iatex footnote s derailed at turnouts. Each accident has been investigated to rank immediate causes, causal factors and contributory factors of derailment at turnouts.

This thesis defines as immediate causes substandard acts or various conditions that lead directly to the derailment. In the event of avoiding or eliminating any immediate causes, associated accidents would be prevented from happening. Likewise, causal factors are any condition, event or behaviour that was necessary for the occurrence of derailment and can be anyone of these factors. However, some conditions, events or behaviours might affect or sustain the occurrence, or exacerbate the derailment (contributory factors). Eliminating one or more of these factors would not prevent derailment, but their presence makes it more likely.

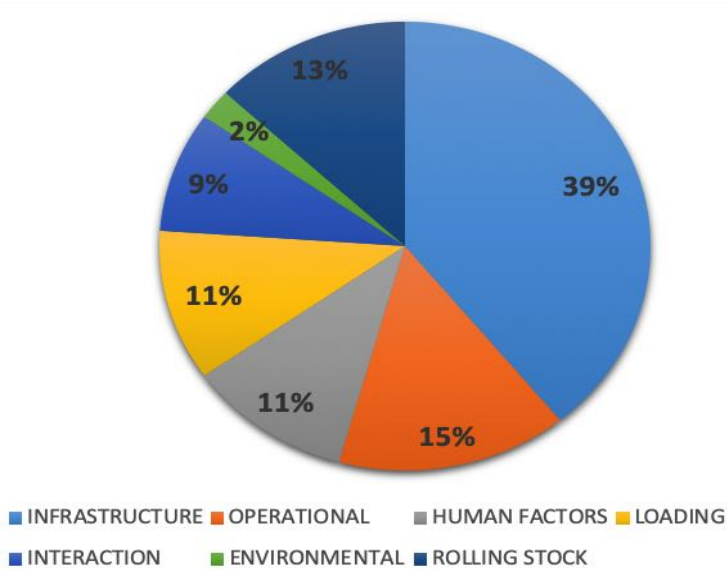

Figure 3.3: Distribution of derailment frequency by various causes

Figure 3.3 illustrates the percentages, by each immediate cause, leading to derailments at turnouts in the UK. Each has several subcategories, as shown in Table 2.1. Some accidents were reported with two or more immediate causes and those were added each by each into analysis in the following Figures and Tables in this chapter.

Infrastructure associated problems, e.g. broken rail and various turnout component failures, have contributed to the majority of derailments. This might be expected due to the fact of the extreme force and potential impact with regard to damages to turnout component as a result of discontinues on the rail line by railway turnout design itself. The results statistically express how vulnerable turnout components are to the forces by rolling stocks. Although the infrastructure failures account for the vast majority of derailment, operational and human factors are almost the same contribution, comprising 39% of accident rates combined. Of the two, 15% were caused by operational failures, while another 11% were caused by human factors. The rest were caused, in order, by loading faults (11%), interaction problems (9%) and environment (13%). As this study is limited by excluding rolling stock-based faults, which demand for a different expertise area (mechanical engineering), there is no discussion in regards to this.

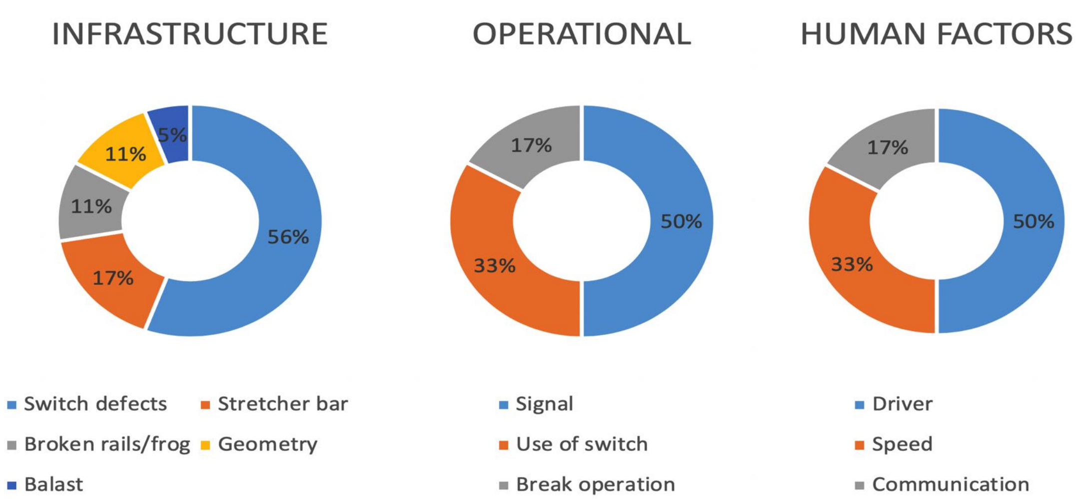

Figure 3.4: Derailment frequency distribution by subcategory-indexed reasons of the top three factors

Derailment frequency distribution by subcategory-indexed reasons of the top three factors. The top three categorised causes, namely infrastructure, operation and human factors, are given in detail in Figure 3.4. Infrastructure-related causes mainly involve various switch defects. The common defects seem to be switch point gapped and switch rod worn, bent, broken, or disconnected. The other infrastructure-related cause is associated with the stretcher bar not working properly. The rest are broken rails and crossing nose, geometry problems and ballast.

Signal problems account for the half of operational-caused derailments. As such, those causes include flagging, improper or failure to flag, or the restrictive indication of a block or interlocking signal or wrong indication of signal. Signal problems were followed by use of switch and braking failures.

Lastly, human-caused derailments are mostly traced back to various driver-centred failures, i.e. failure in not reacting to the 'points not correctly set' indication on the signal or not immediately observing what was displayed by the signal's route indicator. Those are followed by disobeying the permitted speed and communication errors, such as improper radio communication or failure to comply or give/receive.

Aside from immediate causes, causal factors are very important in determining the cause or causes of the derailments so as to prevent further turnout-related accidents of a similar kind. Table 3.3 shows such groups, indicating how responsible each is for derailments. It is evident that derailments at turnouts are mostly a man-made crisis, with maintenance faults, human error and signalling problems accounting for over 50% of accidents. Among these causal groups, maintenance problems appear to be of most interest and need to be reviewed in current maintenance regimes due to the unacceptable frequency of occurrence. With extreme unique internal/external forces, and vulnerability to environmental conditions (as

Table 3.3: Statistical results of causal factors.

Causal Groups	Description	Number of derailments	Percentage
Maintenance	Installation/regime problems, insufficient inspection, undetected bearing/rail welding.	14	32.6%
Environment	Extreme rain, icing/snow on track, high temperature	7	16.3%
Human factors	Vandalism (e.g. by someone placing a stone), slow response to signs or communication	6	13.6%
Track geometry	Significant twist fault, widening has occurred, track gauge failures	5	11.4%
Rolling stock	Degraded bogie/wheel	5	11.4%
Sign	Wrong settlement of points set indicator/related signs, blocked signs	2	4.5%
Malicious	Train lateral/horizontal forces, vulnerable components, design problem	5	9.1%

a common result of the complexity of its geometry), it might be recommended that each individual turnout should be taken into account for maintenance strategies. The railway industry will obtain benefit from this in eliminating risk factors associated with derailments (Dindar and Sakdirat, 2016). Among outer factors, about 16% of derailments were related directly to environmental conditions as causal factors. A recent study (Dindar et al., 2016) has already provided the link between environmental factors, e.g. hot/cold temperature, and derailments at turnouts. Stretcher bars and turnout geometry have also been found to be vulnerable.

Table 3.4 gives information about the distribution of contributory groups analysing the 46 accident reports. The table is prepared to provide insight into how the likelihood or severity of derailments at turnouts escalates. Although some

Table 3.4: Statistical results of contributor groups.

Contributory groups	Description	Number of derailments	Percentage
Maintenance	Lack of detailed inspection, low maintenance frequency, inspection error, inappropriate maintenance plan, etc.	10	20%
Sign/Signal	Location problems, size problems, absence of various aimed signal boxes, etc.	9	18%
Component	Stiffness-related failures, not-fitted-in-use, somewhat out of standard components, etc.	8	16%
Environment	Fog, rain, warm, cold weather patterns, etc.	7	14%
Human errors	Fatigue, mediating drug use, etc.	7	14%
Geometry	The design of the points, the presence of voids, etc.	5	10%
Operational	The failure of the control room, inaccuracy of appointments in inspection, etc.	4	8%

group names in Table 3.4 are the same as those in the previous table, the contents of each are different. For instance, environment is death as a contributory and causal factor. Extreme rain or icing/snow on track or high temperature is thought to directly cause derailment in Table 3.3, whereas moderate environmental patterns, such as low visibility due to fog, are considered to promote derailment accidents.

One of the contributor groups, maintenance, was the most frequently reported category, involved in 20% of all derailment reported by RAIB. This group is mainly built on the concerns described in the Table 3.4. It is seen that a low frequency of maintenance or an inappropriate inspection or the lack of independent inspection is often reported.

On the other hand, sign/signal-related factors were the second most frequently reported group, involved in 18% of all reported accidents. The group mainly concerns the close proximity of points to signal and the absence of an illuminated PSI (points set indicator). Only two accidents are reported by unseen railway lights (due to being blocked by a tree) and small size of railway sign.

Components as a contributor group were the next most frequently reported category, associated with 16% of the accidents. It is mostly reported that, firstly, various rolling stock components, such as a bogie, are not detected to be degraded; secondly, the bolt retaining plates on the field-sides of both switch rails have not been fitted properly; and, thirdly, the lack of support given by the stock rail to the switch because of loose fastenings.

The other groups in the Table 3.4, environment, human error, geometry, and operational, are responsible for some contribution to almost half of the accidents. The details of each are described in the Table 3.4.

3.4 Discussion

The process of analysing risk generally commences with identifying risks and the variety of different contributory factors. This chapter established specific risk groups and then implemented prioritisation to rank them from most to least important. As a result, the findings facilitate the understanding of the risk management/analysis of railway turnout systems in which their immediate, causal and contributory factors must control or alleviate the actualisation of the increased likelihood/consequence of risk incidents.

It has been observed that incidents of train derailment at turnouts are responsible for most accidents that happen on heavy train lines. Even though the traffic density of metro systems (such as the Underground) is approximately the same as heavy lines, the average number of derailments on metro systems is significantly less. Systems of light rail, defined as urban systems of transportation located at ground level, are also found to account for numerous derailments associated with turnouts and it has been determined that they are highly susceptible to this type of accident. Due to the fact that these types of line necessitate specific risk analysis, this chapter has the thesis specifically focus on heavy lines, which appear to have increased exposure to elevated frequencies of derailment.

It is shown that track classification, whether a turnout is in a yard or siding, is investigated to ascertain the extent to which it is correlated with the rate of derailment. Railway vehicles operating on main line tracks are exposed to greater risks in comparison to those in yards, sidings or industrial tracks. Furthermore, as the allowed speed of the turnout is increased, the volume of accidents that occur will grow. Nevertheless, the association between derailment and velocity is marked by its complexity and therefore necessitates additional investigation.

Various causes of accidents are determined to have a powerful association, while others are not. Hence, this thesis is not prepared on the basis of track classification. Accordingly, it can be suspected that that there is a significant relationship between track classification and maintenance issues, based on the difficulties involved in the daily or weekly servicing of turnouts outside urban regions. As the issues related to the standard of work performed by maintenance teams can be varied, a holistic strategy via risk analysis would not be possible. The Chapter 8 will discuss this by emphasising this kind of approach for a specific line rather than the whole railway network.

The primary statistical data on derailment incidents at turnouts is demonstrated in Figures 3.2 to 4 sourced from formal accident reports produced by the Rail Accident Investigation Branch. The leading causes of such incidents are infrastructure, then operational and human errors, respectively. Proportionally, infrastructure has the highest association with the failure of certain turnout constituents. The components that has the highest rate of failure in turnouts has been determined to be the switch, followed by the failures of stretchers. Apart from the turnout component failures, both operational and human flaws appear to be contributory factors in derailment incidents.

Considering the statistical results presented in this chapter, the thesis is established to focus on heavy lines, which is dominant at operational classification, to enhance the data reliability, and respond to majority of derailment accidents. Additionally, one of the objectives of the thesis is to find answers the most frequently occurring types of failure. Therefore, this thesis will propose unique methodologies for analysing derailment risk associated with failures of turnout components, environmental impact and human aspects in the following chapters. Furthermore, environmental impacts will be analysed in relation to the failure of different components to reveal an unknown relation between them and exhibit how to deal with this revealed relation in a risk analysis management.

3.5 Conclusion

Chapter 3 provides fundamental knowledge regarding revealing risk groups designed for derailments at railway turnouts. Moreover, contributory factors are also discussed to find the potential relation between risk groups. As a result, the prioritisation of risks is achieved group by group. Environmental impacts, human errors and component failures are identified to be analysed. These risk groups will be examined in the following chapters.

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CHAPTER 4

BAYESIAN NETWORK-BASED PROBABILITY ANALYSIS OF TRAIN DERAILMENTS CAUSED BY VARIOUS EXTREME WEATHER PATTERNS ON RAILWAY TURNOUTS

4.1 Introduction

Table 4.1 illustrates some significant findings of the Chapter 3. Rolling stock-related failures have been expressed to be excluded from the scope of thesis in Chapter 1, as the field does not fall into civil engineering-centered researches. Additionally, operational problems have been observed to have been investigated in the literature (Cherniak, 2013, Jafarian and Rezvani, 2012). The thesis will propose novel risk analysis methodologies and the findings focusing on human factors and infrastructure-related failures in following Chapters. The Chapter 4 responds to risk investigations associated with environmental impacts on derailments at railway turnouts. The reason of this selection is fundementally to achieve one of thesis objective[1]. In other words, environmental impacts are chosen to find out its relation to infrastructure-related failures. More clearly, the thesis also investigates the relation between two causes, as shown in Table 4.1 (see Section 1.5). As a major component failure, infrastructure-related failures are considered to be part of this investigation as they are more explicitly associated with environmental conditions than the others in Table. 1.

Table 4.1: Distribution of derailment frequency by various causes

Derailment causes	Frequency
Infrastructure related-failures	39%
Operational problems	15%
Rolling stock-related failures	13%
Human factors	11%
Loading	11%
Interaction	9%
Environmental	2%

[1] The establishment of relation between two causal groups.

It has been determined in the Chapter 3 that climatic conditions, such as floods or ice, represent some of the primary causes behind train derailments at turnouts. The effects of environmental factors on railway turnout systems is a relatively novel subject in the related literature and has only been examined by a very few of researchers based on two classifications: Conditional-Based Maintenance (CBM), which merely recommends a prognostic approach to track maintenance (Kaewunruen and Remennikov, 2005, Vale and Ribeiro, 2014), and Risk-Based Maintenance (RBM), which implies that a different or complementary approach should be adopted to reduce the risks that are resulted from various failures and incidents, or errors caused by management deficiencies (Ishak et al., 2016, Saadin et al., 2016). The developments in the first of these categories commences with a basic state-based prognostic technique that is purely aimed at forecasting railway turnout problems (Eker et al., 2011). This study is followed by a statistical examination indicating that a considerable amount of turnout constituent defects could be a result of climatic effects (Hassankiadeh, 2011). Additionally, it might be determined that seasonal variations have significant effects on the prediction of railway turnout failures. Mahoob et al. Mahboob et al. (2012) presented a summary of a series of Component Importance Measures (CIM), formulating the calculation of the CIM utilising Fault Tree Analysis (FTA) and Bayesian Networks (BNs). Recent studies have shown that the impacts of climate on railway turnouts can be assessed on the basis of a failure prediction model founded on Bayesian networks (Wang et al., 2017). Nevertheless, all these actions necessitate the railway sector to comprehend the association between constituent failures and climatic conditions in relation to railway turnouts.

With regard to previous studies on risk, it can be emphasised that following studies frequently intend to fill the gap related with incidents of derailments at railway turnouts. In one study, a probabilistic model was designed to predict rail breakages and to manage the risk of train derailment (Zhao et al., 2007). The categorisation and prioritisation of risks are accomplished for restoring the geometry of railway turnout systems under different operational conditions (Ishak et al., 2016). Dindar et al. Dindar et al. (2016) demonstrated the manner in which turnouts can be impacted by the range of risks caused by natural phenomena and climate change. This study also represented the first to investigate and demonstrate an important relation between train derailments and climatic/weather events. The failure of turnout constituents has been analysed on the basis of various weather patterns (Wang et al., 2017). However, this study was restricted to the failure of constituents by only taking into account precipitation in a specific place and specific rail lines irrespective of the outcomes of these failures, like derailment. Lastly, Dindar and Kaewunruen (Dindar and Sakdirat, 2016) designed a new maintenance strategy on the basis of risk for turnout geometry issues, taking into account different types of failure so as to reduce the likelihood that they will cause derailments.

This chapter proposes a risk analysis for railway turnout systems based on the uncertinity surrounding climatic and environmental factors in order to develop methodical support for decision-making related to the management of derailment problems. Buckley's confidence interval-based technique is utilised to achieve the suggested novel strategy, which has the capacity to model both statistical ambiguity as well as unpredictability and linguistic inexactness.

In order to achieve more suitable, practical and credible outcomes in comparison to traditional and fuzzy techniques, which utilise only one knowledge source, this chapter employs data in relation to 50 states with distinct climatic conditions, on the basis of actual accident reports from the past 10 years. The chapter is structured in the following way: in the methodology section, a short summary of Bayesian networks is presented. Subsequently, an in-depth explanation of fuzzy probability utilising Buckley's method is given. Afterwards, the potential weather trends that increase the risk of derailment are examined, which is followed by a discussion and demonstration of the suggested model and its associated learning algorithm. In the results section, the proposed model is implemented on a railway turnout and the findings are exhibited. Lastly, the discussion section will provide an understanding on how to deal with environmental impacts on derailments at railway turnouts for this chapter.

4.1.1 Weather-related derailments

Although the Table 4.1 shows derailments associated with weather conditions accounts for 2 percent of derailments, they are responsible for a large number of financial losses. Dissimilar to other types of derailment reasons, environmental factor based derailments are frequently not given a necessary attention due to the fact that they occur rarely, and also there is a deficiency in the literature with regard to a thorough comprehension of the underlying effects of weather conditions on derailments associated with turnouts. Hence, it could be claimed that risk management approaches applied to railway turnouts are inadequate considering the requirements of the industry, which causes a serious reduction in the reliability and efficiency of assets, and can lead to fatalities in addition to increased expenditures due to asset failure.

4.1.1.1 Accidents

In this chapter, the definition of derailments related to weather is assumed to be incidents directly by weather conditions or unwanted environmental impacts on the turnout system. This implies that severe weather events, such as high winds, could be responsible for incidents of derailment. Although it is not possible to prevent these occurrences, one can generally forecast their likelihood on the basis of historical data. The additional causes, such as ice or snow on the track, are deduced to be turnout failures, while the reality is that the main cause is the climatic event. It is possible to remedy this situation through the application of certain engineering techniques. Whether the problem can be predicted or remedied, both categories will be addressed in this chapter. The descriptions of accidents contained within formal reports published by the US Federal Railroad Administration have been analysed on the basis of this consideration.

Table 4.2: FRA codes most used in the study

Code	Situation	Primary cause
M101	Changes in condition of a turnout	Snow, ice and mud on track
M102	Extreme environmental condition	Tornado, high wind
M103	Extreme environmental condition	Flood
M104	Extreme environmental condition	Dense fog
M105	Extreme environmental condition	Crosswind
M199	Other extreme environmental conditions	Rarely seen, such as low temperature, flood
T109	Track alignment irregularity	Buckling

Table 4.2 presents a series of codes along with their main causes, with an explanation as to why the derailment happens. The codes are restricted in terms of whether the environmental factor corresponds to an incident of derailment. Accordingly, it has been determined that various flaws in track alignment require focus. As can be observed, certain codes, such as M101, are comprised of a group of main causes, which are distinct from each other. Hence, one cannot utilise the raw codes to make a Bayesian Network due to the fact that there should be a probabilistic relationship between nodes based on some form of causal dependency.

It is also important to note that while M199 is utilised to ascertain the incidents with any cause from M101 to M105, low temperature and flood are considered to be the main causal factors.

4.1.1.2 Causes and risk factors

While the codes enable all details related to the causes and outcomes of every incident to be captured, it is essential to determine the underlying factors that lead to derailed trains. Furthermore, it is critical that analogous causes are categorised for effective management and mitigation. Based on the main causes presented in Table 4.2, the different risk factors that cause train derailments at railway turnout systems are defined below:

Floods, rains and saturated soil - high water levels caused by continous intense precipitation and sudden floods have been determined to be some of the significant weather events that create major problems for railway networks. Washouts, which are the result of adverse natural events in which erosion of the track-bed is caused by the passage of water, can potentially impair ballast, which could be perceived as a severe geometry issue. While they are predominantly observed on plain stretches of rail, it is possible that they could impact turnouts in yards and sidings, specifically in rural areas. It has been demonstrated that mechanical turnouts have a level of susceptibility to geometry issues, and mechanisms that experience these kinds of issues have an increased likelihood of causing incidents of derailment (Ishak et al., 2016). Apart from the problems of washout and runoff, melting snow could also lead to analogous issues on railway turnout bed.

High Wind and Tornadoes - Strong wind conditions are often observed to be a reason behind incidents of train derailments on main line tracks, as they can potentially dislodge train vehicles from the tracks. It is conceivable that railway vehicles are more vulnerable to high winds at turnouts due to the fact that the degree of running safety in terms of crosswind stability generally reduces on curved and adjustable track mechanisms (Hosoi and Tanifuji, 2012).

Snow and Icing - There is a probability that railway turnouts, crossings and rail check flangeways will have exposure to accumulated ice and snow during the winter months, thus negatively impacting the ability to control railway vehicles and augmenting the possibility of derailed trains at railway turnouts. Additionally, both the surface of the stock and running rail as well as the switch blades could be affected by a coating of frost or ice. This can lessen the friction between the rail and wheel, which presents significant risks that could cause the train to slip, slide or lose control at turnouts. Conversely, adverse winter weather, such as icing, could lead to a situation in which the motor in turnout components like signals is deactivated.

Temperature - The rail neutral temperature should be in the range of operational temperatures in which the track does not suffer from longitudinal stress. Excessively high temperatures cause the generation of considerable lateral alignments in both stock and running rails, which frequently leads to derailed trains. Conversely, excessively cold events can also cause derailments, not only as a result of weak tracks and rail breakages/separations, but also the freezing moisture that frequently materialises on rail surfaces.

Slides of Mud and Rocks - The efficient and safe operations of turnout systems are at risk as a result of the flow of mud, snow or rocks caused by adverse weather events. These dangers increase the risk of derailment where the earth beneath or surrounding the turnout shifts due to the cycle of freezing and thawing, intensive precipitation or strong winds.

Dense Fog - In situations where systems of railway signalling are utilised at turnouts, train drivers are notified of the condition of the stretch of rail before them. As there is a strong likelihood that thick fog will significantly diminish visibility, drivers may not only be unable to correctly identify these systems, but they could also not even see turnouts in a timely manner or decelerate. This can lead to train derailments, and thus reduces the safety of train passengers and cargo.

4.1.1.3 Categorisation

As a result of the numerous reasons and contributory factors presented in the last section, the scenarios that lead to train derailments on turnouts have been classified in Table 4.3. In this Table, nodes 1 to 5 address extreme situations. For example, the node R1 denotes the incidence of severe winds, such as strong wind or tornadoes, whereas R2 includes snowfall, which results in track icing or blockages to the moving components of the turnout, or vision impairment because of the dense precipitation.

Conversely, nodes 6 and 7 denote the two different temperature effects; this is because there are two extreme variations of temperature, dissimilar to the other situations described in the Table 4.3, and additionally, in examinations of the statistics on turnout defects caused by weather conditions, it has been found that a large amount of derailment incidents happened at turnouts at times characterised by high/low temperatures.

Table 4.3: Derailment-related nodes, their description and relevant situation for railway turnouts

Node	Description	Relevant situation
R1	Extreme wind	Interaction problems, blockage
R2	Snowfall	Slipping, blockage, vision loss
R3	Fog	Vision loss
R4	Rainfall	Slipping, vision loss, track bed problems, geometry problems
R5	Flood	Track bed problems, blockage, mechanical/electrical based errors
R6	High temperature	Geometry problems
R7	Low temperature	Embrittlement

4.2 Method

4.2.1 Bayesian networks (BNs)

BNs, also known as belief networks, Bayes network or Bayes nets, belong to the family of probabilistic graphical models (PGM), which enable representation and reasoning about an uncertain domain. The nodes in PGM, specifically referred to in BNs as directed acyclic graph (DAG), represent a set of random variables, $\mathrm{V} = \mathrm{X}_1, \ldots \mathrm{X}_\mathrm{i}, \ldots, \mathrm{X}_\mathrm{n}$, from the domain, while the edges between the nodes represent their probabilistic dependencies among the corresponding random variables. Statistical and computational methods allow for estimation of these conditional dependencies in a graph. Thus, BNs utilise from various principles, including graph theory, probability theory, computer science and statistics.

BNs are a set of all parameters in the network. A conditional probability as a parameter in the network is defined through $\Theta_{X_i|\pi_i} = P_{BN}\left(X_i|\pi_i\right)$ for each x_i state of X_i, With a conditional probability and a DAG, a BN defines a joint probability distribution (JPD), also known as "chain rule", for V, which is acquired by the following equation, Eq. (4.1) (Nielsen and Jensen, 2007):

$$\mathrm{P}(V) = \mathrm{P}\left(X_1, \ldots, X_n\right) = \prod_{i=1}^{n} P\left(X_i|\pi_i\right) \tag{4.1}$$

Any node in BNs is likely not to be any parent in the chain. Thus, the node has only marginal distribution, $P\left(X_i\right)$, as being independent of the other variables. Additionally, each node in a BN is associated with a conditional probability, $P\left(X_i|\pi_i\right)$, of any variable X_i, whose parent set, π_i, is present. This conditional

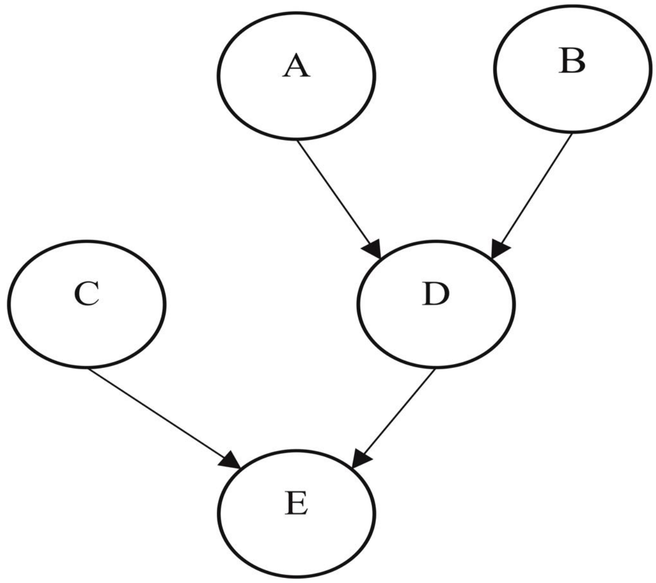


Figure 4.1: A BN for variables A, B, C, D, E.

probability is calculated by following equation, Eq. (4.2) (Nielsen and Jensen, 2007):

$$\mathrm{P}\left(X_i|\pi_i\right) = \frac{\mathrm{P}\left(X_i \cap \pi_i\right)}{P\left(\pi_i\right)} \tag{4.2}$$

Considering the BNs in Fig. 4.1, the full joint probability distribution of this BN might be simplified as

$$P(A, B, C, D, E) = P(A)P(B)P(C)P(D|A, B)P(E|C, D) \tag{4.3}$$

Conditional and marginal probability distributions of these variables are presented in 5.3 to 5.7. A, B and C are classified only in Marginal Probability Tables 4.3, 4.4 and 4.5 as they do not have a parent node. On the other hand, conditional probability distributions of D and E are generated in Table 4.6 and 4.7.

The joint probability of this BN is calculated with the following Eq.:

$$P\left(a_i b_j c_k d_l e_n\right) P(A = a_i, B = b_j, C = c_k, D = d_l, E = e_n) \\ = p_{a_i} p_{b_j} p_{c_k} \frac{p_{a_i} p_{b_j} p_{d_l}}{p_{a_i} p_{b_j}} \frac{p_{c_k} p_{d_l} p_{e_n}}{p_{c_k} p_{d_l}} \tag{4.4}$$

This determination of marginal and conditional probability tables enables probabilities for these variables, e.g. $P(A|B), P(A|D)$, to be calculated.

Table 4.4: Marginal probability table for A

$P\left(A = a_1\right)$	$P\left(A = a_2\right)$
pa_1	pa_2

Table 4.5: Marginal probability table for B

$P\left(B = b_1\right)$	$P\left(B = b_2\right)$
pb_1	pb_2

Table 4.6: Marginal probability table for C

$P\left(C = c_1\right)$	$P\left(C = c_2\right)$
pc_1	pc_2

Table 4.7: Conditional probability table for D

A	B	$P\left(\left(D = d_1\right)\|A, B\right)$	$P\left(\left(D = d_2\right)\|A, B\right)$
a_1	b_1	$\frac{p_{a_1,b_1,d_1}}{p_{a_1,b_1}}$	$\frac{p_{b_1,b_1,d_2}}{p_{b_1,b_1}}$
a_2	b_1	$\frac{p_{a},b_1,d_1}{p_{a_2,b_1}}$	$\frac{p_{a_2,b_1,d_2}}{p_{a_2,b_1}}$
a_1	b_2	$\frac{p_{a_1,b_2,d_1}}{p_{a_1,b_2}}$	$\frac{p_{a_1,b_2,d_2}}{p_{a_1,b_2}}$
a_2	b_2	$\frac{p_{a_2,b_2,d_1}}{p_{a_2,b_2}}$	$\frac{p_{a_2,b_2,d_2}}{p_{a_2,b_2}}$

Table 4.8: Conditional probability table for E

C	D	$P\left((E=e_1)\,\vert C,D\right)$	$P\left((E=e_2)\,\vert C,D\right)$
c_1	d_1	$\frac{p_{c_1,d_1,e_1}}{p_{c_1,d_1}}$	$\frac{p_{c_1,d_1,e_2}}{p_{c_1,d_1}}$
c_2	d_1	$\frac{p_{c_2,d_1,e_1}}{p_{c_2,d_1}}$	$\frac{p_{c_2,d_1,e_2}}{p_{c_2,d_1}}$
c_1	d_2	$\frac{p_{c_1,d_2,e_1}}{p_{c_1,d_2}}$	$\frac{p_{c_1,d_2,e_2}}{p_{c_1,d_2}}$
c_2	d_2	$\frac{p_{c_2,d_2,e_1}}{p_{c_2,d_2}}$	$\frac{p_{c_2,d_2,e_2}}{p_{c_2,d_2}}$

4.2.2 Fuzzy probability

4.2.2.1 Preliminaries

This section sets up the terminology and notation that is not part of the technical contribution, but is needed to delineate material of the chapter.

Definition 1. the membership function of an element, x, is $\mu_{\widetilde{A}}(x)$. The element belongs to a fuzzy set $\widetilde{A}$, where each element of x is always mapped to a value between 0 and 1, i.e. $0 \leq \mu_{\widetilde{A}}(x) \leq 1$ (Dubois, 1980).

Definition 2. A fuzzy number $\widetilde{A}$ is a fuzzy set on **R**. $\mu_{\widetilde{A}}(x)$ is a membership function (Dubois, 1980) such that

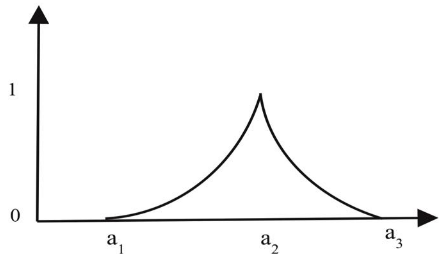
i. The α-cut of a fuzzy set $\widetilde{A}$ is closed intervals of **R** and denoted as the crisp set A_α given by $A_\alpha = \left\{x \in X : \mu_{\widetilde{A}}(x) \geq \propto\right\}$ where $0 \leq \propto < 1$.

ii. A fuzzy set $\widetilde{A}$ is said to be convex due to

$$\mu_{\widetilde{A}}\left(\lambda x_1 + (1-\lambda)x_2\right) \geq \min\left(\mu_{\widetilde{A}}\left(x_1\right), \mu_{\widetilde{A}}\left(x_2\right)\right) \text{ for } \lambda \in [0,1]$$

Defination 3. α -cut FN is a fuzzy number $\widetilde{A}$ by the triplet $\widetilde{A} = a_1, a_2, a_3$ with the shape of concave function if its membership function $\mu_{\widetilde{A}}(x)$ is given by Buckley (2006):

Defination 3. The mathematical operations of two TFNs, $\widetilde{X}(\alpha) = [a_1, b_1]$ and $\widetilde{Y}(\alpha) = [a_2, b_2]$ are as follows (Buckley, 2006, Dubois, 1980):



$$\mu_{\widetilde{A}}(x) = \begin{cases} 0 & for\ x < a_1 \\ \frac{x-a_1}{a_2-a_1} & for\ a_1 < x < a_2 \\ \frac{a_3-x}{a_3-a_2} & for\ a_2 < x < a_3 \\ 0 & for\ a_3 < x \end{cases}$$

- $\widetilde{X}(\alpha) + \tilde{Y}(\alpha) = [a_1, b_1] + [a_2, b_2] = [a_1 + a_2, b_1 + b_2]$
- $\widetilde{X}(\alpha) - \tilde{Y}(\alpha) = [a_1, b_1] - [a_2, b_2] = [a_1 - b_2, b_1 - a_2]$
- $\widetilde{X}(\alpha) \cdot \widetilde{Y}(\alpha) = [a_1, b_1] \cdot [a_2, b_2] = [\min(a_1 \cdot a_2, a_1 \cdot b_2, b_1 \cdot a_2, b_1 \cdot b_2), \max(a_1 \cdot a_2, a_1 \cdot b_2, b_1 \cdot a_2, b_1 \cdot b_2)]$
- $\widetilde{X}(\alpha)/\widetilde{Y}(\alpha) = [a_1, b_1] / [a_2, b_2] = [a_1, b_1] \cdot \left[\frac{1}{b_2} \frac{1}{a_2}\right]$

4.2.2.2 Probability of fuzzy events

A random variable x is in a sample space X. Then, a crisp event is defined as a subset of A, and its unconditional probability $\Pr(A)$ is calculated by the following Eq.:

$$\Pr(A) = \int_{x \in A} f(x)dx = \int_{-\infty}^{+\infty} X_A(x) f(x)dx \tag{4.5}$$

where $X_A(x)$ is a membership of an element in a subset A of X, a binary indicator function with the value 0 for all elements of X not in A and the value 1 for all elements of A.

On the other hand, it has been expressed in previous section that the indicator functions $X_A(x)$ of fuzzy events are their membership functions,$\mu_{\widetilde{A}}(x)$. Thus,

$X_A(x)$ in the Eq. can be replaced with $\mu_{\widetilde{A}}(x) : X \to [0, 1]$, as such:

$$\Pr(A) = \int_{-\infty}^{+\infty} \mu_{\widetilde{A}}(x) f(x) dx \tag{4.6}$$

Eq. 4.6, that is, estimate a fuzzy probability density function through the product $\mu_{\widetilde{A}}(x)f(x)$.

4.2.2.3 Fuzzy estimation based on Buckley's method

The method is quite a new application to the BN for risk calculation of engineering systems, but it is proposed that Buckley's approach might be one of the best solution to rare events within a scarce data environment (Ersel and İçen, 2016). To calculate probability on the basis of fuzzy knowledge, Buckley proposes two approaches defining the probability as a triangular-shaped fuzzy number. The differences between the two relates to the source of knowledge from which the statistical model for probability estimate is utilised. In the first approach, a1, a2 and a3 values are defined in accordance with expert opinions, while the other deals with data, considering suitable confidence intervals to uncertainities in the clusters.

This approach has long been used by various scholars interested in only two possible outcomes, labelled 'success' and 'failure'. Let p be the probability of a success and x be the number of times we had a success in n independent repetitions of an experiment. Therefore, if we want to estimate the value of probability p based on this approach, then a random sample, which, here, is running the experiment 'n' independent times, i.e. $\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{n}$, should be gathered. The probability density function of this experiment is defined as $f(x, p)$.

Based on this experiment, p, as a single unknown parameter, is calculated with interval cuts. The thesis makes $100(1-\propto)\%, 0 \leq \alpha \leq 1$, confidence intervals for p . These confidence intervals are donated $[\mathrm{p}_1(\propto), \mathrm{p}_2(\propto)]$. Moreover, these confidence intervals are nested. The confidence intervals are then placed on top of one another in the way of $\propto= 0$ to $\propto= 1$ in order to create a fuzzy number p , whose α-cuts are the confidence intervals. The mathematical progress of a fuzzy number is explained as follows:

It is known that $\hat{p}-p=\sqrt{p-\left(\frac{1-p}{n}\right)}$, where $\hat{p}$, equals to x/n,donates the point of estimation and also n donates the number of independent repetitions, roughly $N(0,1)$ if n iss sufficiently large. Thus,

$P\left(\hat{p}-z_{\beta/2}\sqrt{\hat{p}(1-\hat{p})/n} \leq p \leq \hat{p}+z_{\beta/2}\sqrt{\hat{p}(1-\hat{p})/n)}\right) \approx (1-\beta)$

The equation above leads to the $(1-\beta)100\%$ approximate confidence interval for p

$$\left[\widehat{p}-z_{\beta/2}\sqrt{p(1-p)/n}, \hat{p} \leq \hat{p}+z_{\beta/2}\sqrt{p(1-p)/n}\right] \tag{4.7}$$

Therefore, $(1-\beta)100\%$ confidence intervals for each β might be found. This gives p, and β is suggested to be between 0.01 and 1. In accordance with this range, these intervals can be presented as $\left[p^L(\beta), p^U(\beta)\right]$.

To produce a triangular-shaped fuzzy number $\overline{p}$ whose $\alpha-$cuts are the confidence intervals, we can place these confidence intervals in the way of one over another with the following equation for $0.01 \leq \beta \leq 1$.

$$\widetilde{P}(\propto) = \left[p^L(\propto), p^U(\propto)\right] \tag{4.8}$$

This allows for gathering more information in $\overline{p}$ than just a single confidence interval or just a point estimate. Thus, $\overline{p}$, which is a triangular-shaped fuzzy number, will be the fuzzy estimator for p.

4.2.3 Bayesian Network model and probability assessment

4.2.3.1 FBN-based probability assessment frame

There is a long record of weather-caused derailments at turnouts, which has enhanced the knowledge of what causes most give rise to derailment. However, we have no idea regarding the interaction of these causes or about what the probability distribution is going to be like in a situation in which one of these causes is impossible to happen, e.g. tornado in areas with mild climate. Hence, there is a need for a generic BN-based weather-caused flow diagram to be developed.

For the implementation of weather-related derailment estimates at turnouts, a systematic Bayesian Network is developed, as seen in Fig. 4.2.

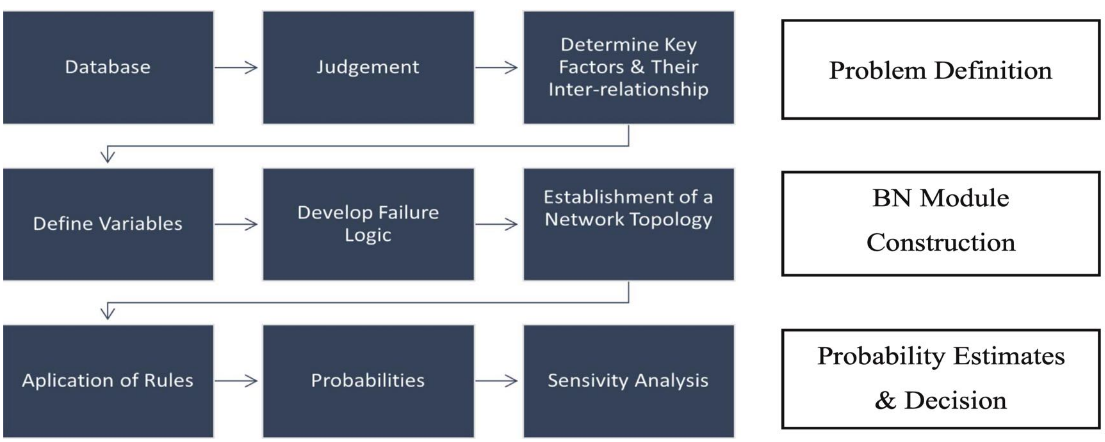


Figure 4.2: The novel framework of Bayes Network-based derailment prediction for railway turnouts

In this proposed approach, the following three steps are adopted:

- Step (1) Problem definition: Carry out a search of available databases which refer to all kinds of weather-related derailments; judge data in order to identify all anticipated weather-based causes/factors to potential derailment accidents at turnouts; pay attention to causal relationships among those causes/factors. Step 1 is revealed in detail in the intrduction.

- Step (2) BN module construction: Define both variables (nodes) having a finite set of mutually exclusive states as identified root nodes (RNs) or intermediate nodes (INs) to represent the identified hazards; develop failure logic through conditional probability distribution (CPD); establish a network topology to describe conditional independence relationships of defined variables. Step 2 is archived in the following sub-headings in this section.

- Step (3) Probability estimates and decision: Specify states and assign input values for probability estimation of RNs; calculate probabilities based upon Buckley's alpha cut methods via Eq. 4.7.; update the values of all nodes by calculating posterior probabilities; perform sensitivity analysis to reveal the performance of each variable's contribution to the occurrence of a derailment accidents at turnouts. Step 3 is discussed in the Section Discussion.

4.2.3.2 The Bayesian Network structure of weather-related derailments

The failure-consequence scenarios from the top to bottom nodes using a directed acyclic graph (DAG) are created through the logic diagram in accordance with the accidents reports. Thus, a weather-related derailment Bayesian Network (WRDBN) is established through steps 1 and 2 in Fig. 4.2. WRDBN, as seen in Fig. 4.3, is formed of 11 root nodes, which are addressed to intermediate nodes, contributing to the leaf node, derailment. Intermediate nodes have been described as relevant stations in Table 4.3. Root nodes, intermediate nodes and the leaf node are encoloured into grey, orange and red in Fig. 4.3, respectively.

The descriptions of all nodes illustrated in Fig. 4.3 are given in Table 4.9. The intermediate nodes are added in accordance with primary causes in the accident records. For instance, high wind (R_1) is shown as a root cause giving rise to inadequacies in a railway turnout management system that allows the immediate causes (I_1, I_2) to arise unchecked, leading to the accidents. The intermediate nodes and their relations to root causes are revealed as result of investigation of over 17,000 accident reports between 2006 and 2015. Intermediate nodes firstly aim at identifying what kinds of areas impacted by weather patterns at turnouts, and, secondly, to investigate to what degree the patterns effect on the intermediate nodes in comparison with the other cases with non-environmental reasons.

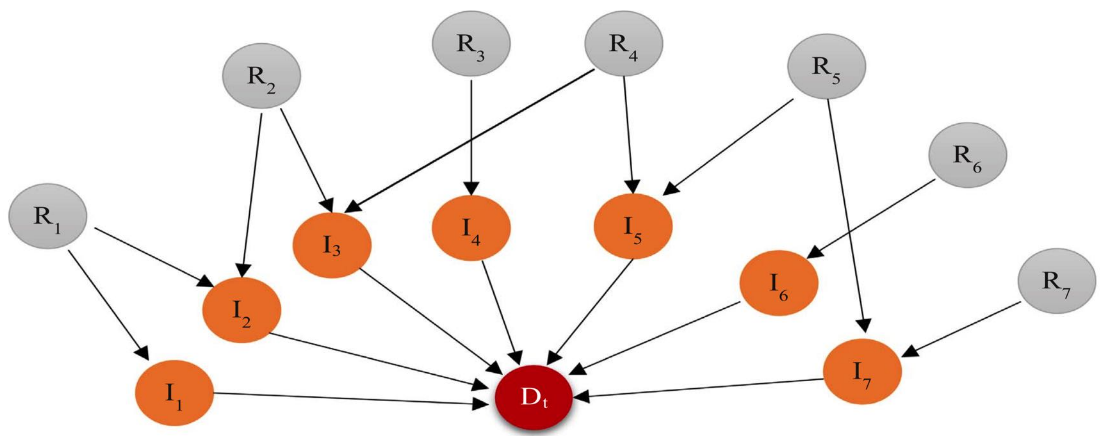


Figure 4.3: Established BN model for WRDBN

As an example, obstructions (I_2) is determined to be one of the most common causes encountered at railway turnouts, and to be formed by not only frozen precipitation (R_2), including snowfall, hail, etc., but also wind (R_1), often blowing debris and trees from the trackside and from neighbouring land onto turnouts. To calculate conditional probabilities, the other cases, such as maintenance errors, vandalism, etc., as well as these two causes-related cases, are considered. In other words, even if either R_1 or R_2 does not present, a derailment as the result of any obstruction is likely to happen. Therefore, each accident report has been

Table 4.9: Variables in WRDBN

Node	Nodes	Description
R_1	Root	Extreme wind
R_2	Root	Frozen precipitation
R_3	Root	Fog
R_4	Root	Liquid precipitation
R_5	Root	Flood
R_6	Root	High temperature
R_7	Root	Low temperature
I_1	Intermediate	Aerodynamic problems
I_2	Intermediate	Obstructions
I_3	Intermediate	Slipping
I_4	Intermediate	Vision loss
I_5	Intermediate	Track bed problem
I_6	Intermediate	Geometry problem
I_7	Intermediate	Component failures
D_1	Leaf	Derailment

examined in details to find absolute answers regarding to the relation between derailment and environmental effects, and to what degree these environmental effects take place in derailments at railway turnout systems.

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4.3 Results

4.3.1 Marginal and conditional probability assessment

In contrast to utilising the subjective data by means of a review/ interview-based dataset, this chapter only relies on absolute data of derailment cases collected in the United States for the period between 2005 and 2015. This enables data rigidity to be less difficult to demonstrate and assess than that offered by subjective data. As a result, the engineering problem (establishing an updatable risk analysis method) and the purpose of the analysis (ranking and identifying environmental impacts on derailments) are demonstrated with concrete data validity. To identify environmental impacts, a fuzzy-logic Bayesian network, which is designed uniquely for the purpose of the risk analysis, is used as the risk analysis model. Through this proposed model, marginal probabilities of the weather-based events are calculated, considering all accident cases occurring at railway turnout systems. Thus, a marginal probability of an event presents an idea of how likelihood a derailment happens in comparison to the other weather-based events.

Table 4.10 shows lower and upper marginal probabilities of three events, including R_1, R_2 and R_5. The Table is prepared in accordance with the recommended instructions in Section 2, while values against each α-cut are calculated by Eq. (4.7), and then tabulated through Eq. (4.8). These calculations are executed by MATLAB ver.2016b (see Appendix A).

As seen in Table 4.10, marginal probabilities in the network are binary with true and false values e.g. $\widetilde{P}\left(\mathrm{R1} = \mathrm{r1}_1\right)(\alpha)$, $\widetilde{P}\left(\mathrm{R1} = \mathrm{r1}_2\right)(\alpha)$, respectively. In order to make sure and present the behaviours of lower and upper probabilities, α -cuts are aligned with intervals of 0.2.

Table 4.10: Marginal probabilities for 'extreme wind', 'frozen precipitation' and 'flood' causing derailment at turnouts.

	$\widetilde{P}\,(\mathrm{R1} = \mathrm{r}_1)\,(\alpha)$		$\widetilde{P}\,(\mathrm{R1} = \mathrm{r1}_2)\,(\alpha)$	
	$p^{L}_{r1_1}(\alpha)$	$p^{U}_{rl_1}(\propto)$	$p^{L}_{r1_1}(\propto)$	$p^{U}_{r1_2}(\alpha)$
$Alpha - Cuts$				
0.00	0.24709	0.27077	0.72923	0.75291
0.20	0.25304	0.26482	0.73518	0.74696
0.40	0.25506	0.26280	0.73720	0.74494
0.60	0.25652	0.26134	0.73866	0.74348
0.80	0.25776	0.26009	0.73991	0.74224
1.00	0.25893	0.25893	0.74107	0.74107
	$\widetilde{P}\,(\mathrm{R2} = \mathrm{r2}_1)\,(\alpha)$		$\widetilde{P}\,(\mathrm{R2} = \mathrm{r2}_2)\,(\alpha)$	
	$p^{L}_{r2_1}(\propto)$	$p^{U}_{r2_1}(\alpha)$	$p^{L}_{r2_2}(\propto)$	$p^{U}_{r2_2}(\propto)$
$Alpha - Cuts$				
0.00	0.46864	0.49565	0.50435	0.53136
0.20	0.47542	0.48886	0.51114	0.52458
0.40	0.47773	0.48655	0.51345	0.52227
0.60	0.47939	0.48489	0.51511	0.52061
0.80	0.48081	0.48347	0.51653	0.51919
1.00	0.48214	0.48214	0.51786	0.51786
	$\widetilde{P}\,(\mathrm{R5} = \mathrm{r5}_1)\,(\alpha)$		$\widetilde{P}\,(\mathrm{R5} = \mathrm{r5}_2)\,(\alpha)$	
	$p^{L}_{r5_1}(\alpha)$	$p^{U}_{r5_1}(\alpha)$	$p^{L}_{r5_2}(\alpha)$	$p^{U}_{r5_2}(\propto)$
$Alpha - Cuts$				
0.00	0.07301	0.08770	0.91230	0.92699
0.20	0.07670	0.08401	0.91599	0.92330
0.40	0.07796	0.08276	0.91724	0.92204
0.60	0.07886	0.08185	0.91815	0.92114
0.80	0.07963	0.08108	0.91892	0.92037
1.00	0.08036	0.08036	0.91964	0.91964

Aside from marginal probability calculations, seven intermediate nodes and one leaf node are revealed to identify to what degree the notion of degree of belief in their occurrence was conditional on a body of knowledge in WRDBN. The calculation of all conditional probabilities is executed through Eq. (4.2) in compliance with the Bayes rules given in Section 4.2.2. Eqs. (4.7) and (4.8) are utilised to calculate and tabulate the probabilities.

I_1 and I_4 out of those nodes are presented in Table 4.12. According to the nature of conditional probabilities, it is attempted to find all variations of the events. For instance, I_1 responds to aerodynamic problems and is composed of a root node (R_1) (see Section 4.2.1). Additionally, a derailment is likely to take place, regardless of this rood node, through tornadoes (see Section 4.1.1). Therefore, the probability of an event's occurrence given that another event has already happened or not happened is revealed through accident reports.

4.3.2 Prior and posterior probabilities for WRDBN

Prior probabilities of nodes in WRDBN are the original probabilities of an outcome, which is only related to environmental-based,(i.e. weather), derailments at railway turnout systems, and will be updated with new information to create posterior probabilities.

To identify whether the unequal proportions across nodes present a real difference in the true population or whether the difference is a result of sampling error, prior probabilities that greatly affect the accuracy of results in WRDBN are specified and illustrated in Fig. 4.4. Red bars show the prior-based likelihood of occurrence of a derailment in the nodes, while α-cuts equals to '1.00'. I_2, obstructions, seems to be an intermediate node, causing mostly a weather-related derailment at railway turnout systems, followed by I_3, slipping, and I_5, trackbed

Table 4.11: Conditional probabilities for 'Aerodynamic Problems' (I_1) and 'Vision loss' (I_4) causing derailment at turnouts.

	$\widetilde{P}(I1 = I1_1 \mid R1)(\alpha)$				$\widetilde{P}(I1 = I\mathbf{1}_2 \mid R1)(\alpha)$			
	$p^L_{I1_1,R1_1}(\propto)$	$p^U_{I1_1,R1_1}(\propto)$	$p^L_{I1_1,R1_2}(\propto)$	$p^U_{I1_1,R1_2}(\propto)$	$p^L_{I1_2,R_1}(\propto)$	$p^U_{I1_2,R1_1}(\propto)$	$p^L_{I1_2,R1_2}(\propto)$	$p^U_{I1_2,R1_2}(\propto)$
$Alpha - Cuts$								
0.00	0.40048	0.42710	0.00646	0.01156	0.57290	0.59952	0.98844	0.99354
0.20	0.40717	0.42041	0.00774	0.01028	0.57959	0.57959	0.98972	0.99226
0.40	0.40945	0.41814	0.00817	0.00984	0.58186	0.59055	0.99016	0.99183
0.60	0.41108	0.41650	0.00849	0.00953	0.58350	0.58892	0.99047	0.99151
0.80	0.41248	0.41510	0.00876	0.00926	0.58490	0.58752	0.99074	0.99124
1.00	0.41379	0.41379	0.00901	0.00901	0.58621	0.58621	0.99099	0.99099

	$\widetilde{P}(I4 = I4_1 \mid R4)(\alpha)$				$\widetilde{P}(I4 = I4_2 \mid R4)(\alpha)$			
	$p^L_{I4_1,R4_1}(\propto)$	$p^U_{I4_1,R4_1}(\propto)$	$p^L_{I4_1,R4_2}(\propto)$	$p^U_{I4_1,R4_2}(\propto)$	$p^L_{I4_2,R4_1}(\propto)$	$p^U_{I4_2,R4_1}(\propto)$	$p^L_{I4_2,R4_2}(\propto)$	$p^U_{I4_2,R4_2}(\alpha)$
$Alpha - Cuts$								
0.00	0.48649	0.51351	0.00646	0.01156	0.48649	0.51351	0.98844	0.99354
0.20	0.49328	0.50672	0.00774	0.01028	0.49328	0.50672	0.98972	0.99226
0.40	0.40945	0.50441	0.00818	0.00984	0.49559	0.50441	0.99016	0.99183
0.60	0.49725	0.50275	0.00849	0.00953	0.49725	0.50275	0.99047	0.99151
0.80	0.49867	0.50133	0.00876	0.00926	0.49867	0.50133	0.99074	0.99124
1.00	0.50000	0.50000	0.00901	0.00901	0.50000	0.50000	0.99099	0.99099

problems. On the other hand, I_4, vision loss, and I_7, component failures, are the rarest learned events in WRDBN.

It is seen also from Fig. 4.4 that most of the weather-related causes have often resulted in derailments at turnouts. However, almost one-sixth of derailments happened as a result of those, since other causes except weather-based ones could give rise to derailments as well. A posterior probability is the probability of assigning observations to groups given the data, and is one of the underlined steps in the Bayes Network framework, as shown in Section 4. It might be significant to understand how the prior probabilities change when a new observation is added into the BN for leaf node. It is supposed that D_t, derailment at turnouts, is observed to take place, which is notated as $\widetilde{P}\left(D_t = 1\right)\left(\alpha_{1.00}\right)$.

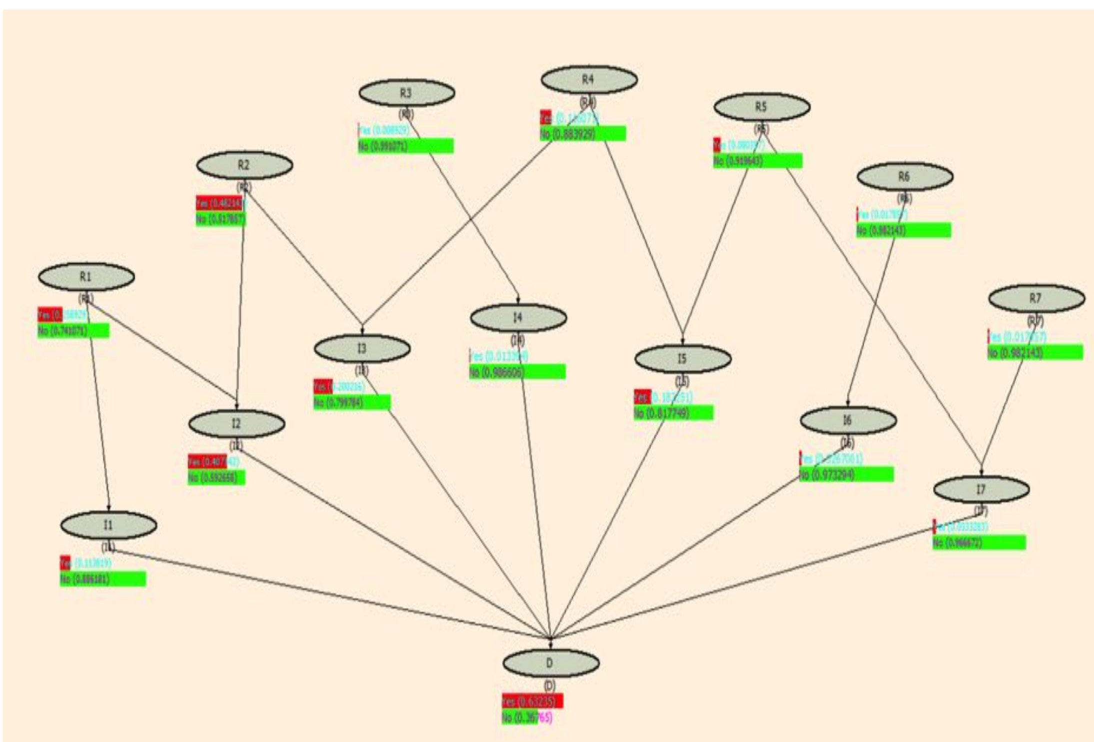

Figure 4.4: The distribution of P prior (α) of the root, intermediate and leaf node in WRDBN towards α -cuts = 1.

Fig. 4.6 shows four prior probabilities, $\widetilde{P}\left(R1 = r1_1\right)(\alpha)$, $\widetilde{P}\left(R1 = r2_1\right)(\alpha)$,

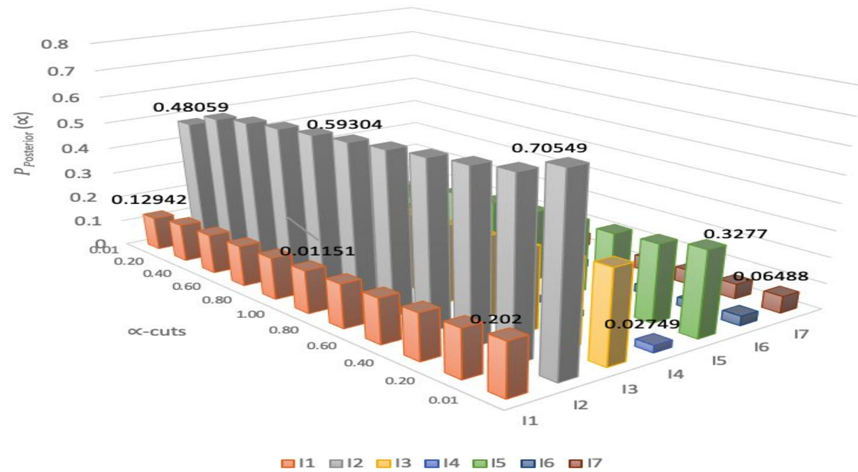

Figure 4.5: The distribution of P posterior (α) of the intermediate nodes and the leaf node in WRDBN towards α-cuts.

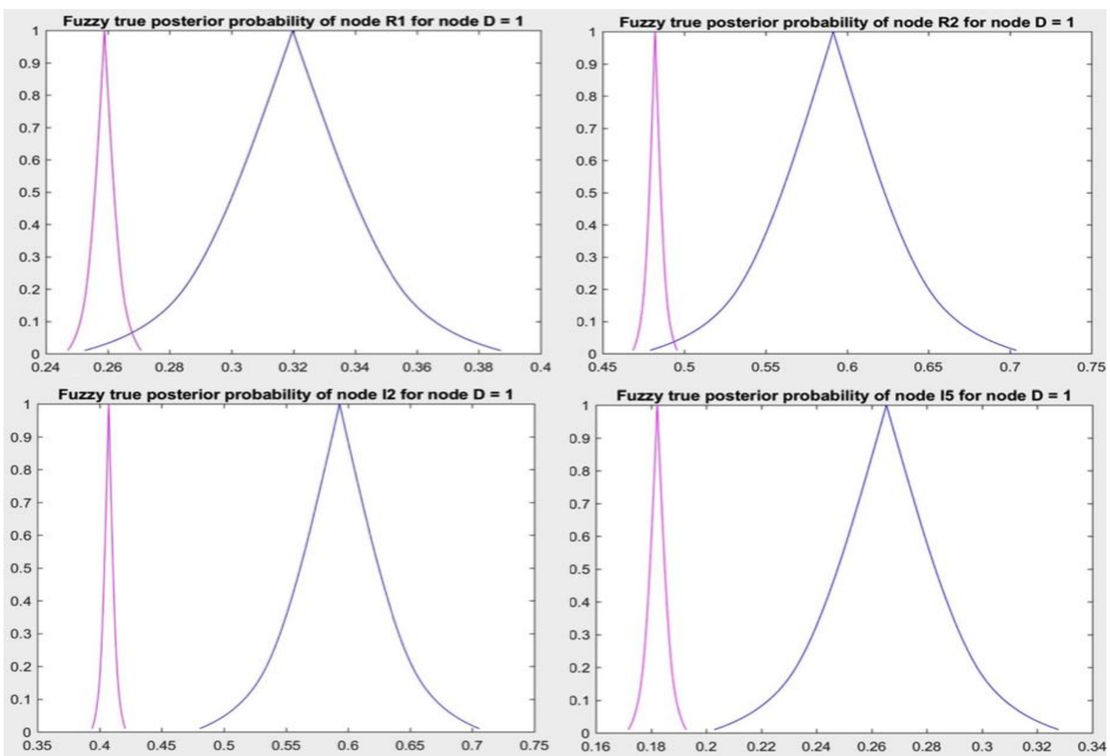

Figure 4.6: Prior fuzzy probabilities and posterior fuzzy probability of R1, R2, I2 and I5 in WRDBN.

$\widetilde{P}\left(I2 = i2_1\right)(\alpha)$, $\widetilde{P}\left(I5 = i5_1\right)(\alpha)$, and four posterior probabilities, $\widetilde{P}\left(R1 = r1_1|D = 1\right)(\propto)$, $\widetilde{P}\left(R2 = R2_1|D = 1\right)(\propto)$, $\widetilde{P}\left(I2 = I2_1|D = 1\right)(\alpha)$,

$\widetilde{P}\left(I5 = I5_1|D = 1\right)(\alpha)$ in WRDBN. The prior probability distribution is coloured in magenta, while the posterior probabilities are shown as blue lines in the Figure 4.6. As marginal probabilities are prior probabilities in BNs, the distribution is matched with Table 4.10, given in Section 4.3.1. These nodes are found to be the most changing ones, given D equals to 1. The peak of lines occurs when α-cut is 1.00, which gives rise to 0 confidence interval. On the other hand, the higher the values of confidence intervals get, the lesser $\alpha-$ cuts are valued. This provides an opportunity to railway operators, when the uncertainty of any event in WRDBN is high, and the small values of α-cuts are taken. This is because probability intervals get larger and, as result, information loss is prevented. In contrast, when a database gives concrete information on an event history, it will be better to opt for the high values of α -cuts, which makes probability intervals narrower and, so, results in a more realistic response to investigation.

4.3.3 Sensitivity analysis

In this chapter, a preliminary conclusion (i.e. node 'derailment at turnouts due to the reasons in Table 4.7' is considerably sensitive to node 'frozen precipitation') can be drawn based on posterior probabilities, e.g. $\widetilde{P}\left(R2 = R2_1|D = 1\right)(\alpha)$. Therefore, the sensitivity analysis is performed, inputting the different rational parameters values in order to monitor the impact of these changes on the posterior probabilities through a number of membership functions, $\mu\widetilde{R_2}(x)$.

In WRDBN, the marginal probability of this node, $\widetilde{P}\left(\mathrm{R2} = \mathrm{r2}_1\right)(\alpha)$, has been found as 0.48214. As a result, the range is kept as large as possible in order to give an idea as to how sensitive the model's performance is to a large range of changes in the input parameters. To reach the results of nine different values, an in-house developed MATLAB program (see Appendix A) has been implemented into the FBN inference.

Fig. 4.7 illustrates these results, showing the confidence-based probability distribution of R2 towards the various variations of node R2 from 0.1 to 0.9. As seen in the Figure 4.7, each peaking curve indicates that $\widetilde{P}\left(R2 = r2_1|D = 1\right)(\alpha)$ clearly changes with $\widetilde{P}\left(\mathrm{R2} = \mathrm{r2}_1\right)(\alpha)$. It is also shown that there is a positively increasing trend in the posterior probabilities of node R2 when $\widetilde{P}\left(\mathrm{R2} = \mathrm{r2}_1\right)(\alpha)$ steadily increases. Thus, this Figure presents an evidance to show that the above conclusion is reliable and reasonable.

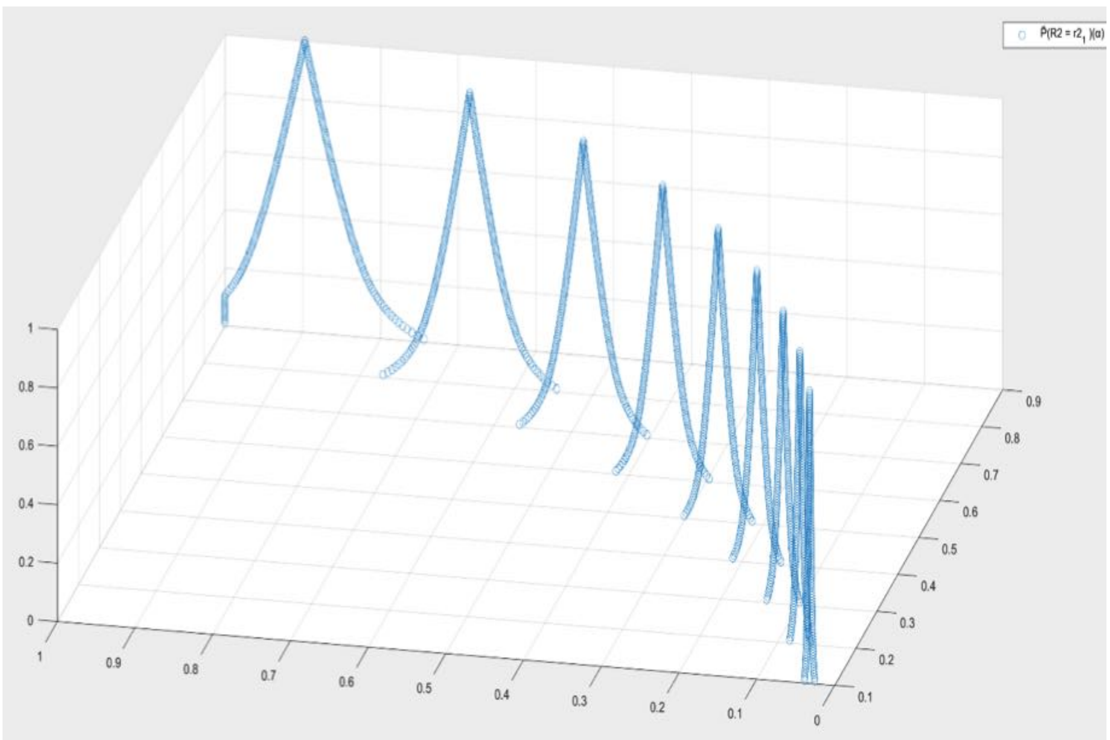

Figure 4.7: Sensitivity analysis for $\mu_{\widetilde{R}_2}(x)$ of $\widetilde{P}\left(R2 = r2_1\right)(\alpha)$ in WRDBN, corresponding to $\widetilde{P}\left(R2 = r2_1|D = 1\right)(\alpha)$

On the other hand, the results match, reasonablly, with the previous statement *'the higher the values of confidence intervals get, the less α-cuts are valued'*. As node R2 is inputted with higher values, the confidence intervals affact much higher on the probability distribution towards alpha-cuts, which stresses how uncertain the node is.

4.4 Discussion

FBN is quite a prominent technology with huge potential for various applications across many engineering domains. This study discusses FBN and its application in railway turnout systems. The proposed FBN approach, namely WRDBN, uses the probabilities of environmental-related causes of accidents to perform Bayesian inference, which is established by causal relationship through accident reports. Therefore, the BN provides the model structure of WRDBN, fuzzy prior probability and likelihood calculation, and inference and interpretation. Aside from the BN, there have been many other techniques which are suggested to risk, occurrence or consequence analysis of any type of accident across railway systems. Fuzzy fault tree analysis (FFTA) currently seems to be one of the common methods for turnout, along with the other railway engineering systems (Huang et al., 2000, Ishak et al., 2016, Jafarian and Rezvani, 2012, Peng et al., 2016). One of the main differences between those FFTAs and this proposed FBN is that FBN might be more capable to handle the causal relations in a complex environment, including many engineering works, e.g. trackbed, aerodynamic, adhesion, because FFTAs are mainly comprised of simple Boolean functions such as AND-gate and OR-gate while FBN is based on different causal relationships, in particular considering its conditional probability calculation.

Derailments at railway turnouts yield serious consequences, including loss of life, operational shutdown and damage to railway assets. Although these derailments account for one-third of all derailments on lines, those that are weather-related are quite rare events. As a result, this chapter only focuses on weather-related accidents to understand what types of causes are dominant in a particular scenario. Frozen precipitation is observed to be considerably responsible for such accidents, which gives rise mainly to preventing proper movement of switch blades. From the perspective of sensitivity analysis, the structure of the proposed WRDBN is observed to produce a reliable and reasonable measure of performance of this node. The probabilities have been extracted and calculated by means of oficial accident reports over the years between 2006 and 2015 across the US. WRDBN only gives an idea on the risk elements associated with weather ,which lead to derailments at various types of railway turnout derailments. Due to the United States' 9.9 million km^2 area and mid-continental placement, the country has a widely varying climate, which is unique to understand the impact of different climate patterns on railway turnouts. However, as climate varies on the basis of its prevailing geography, it should be expected that the weather characteristics of different countries lead to different marginal and conditional probabilities of the nodes altshough the structure of BN is established in the same way, as presented in Fig. 4.2.

4.5 Conclusion

Chapter 2 has revealed how effective a Bayesian network could be to achieve thesis objective. Additionally, environmental impacts are identified by Chapter 3 to be one of the causal group responsible for train derailments at railway turnouts. Therefore, this chapter proposes a novel Bayesian network to deal with risk of derailment associated with environmental impacts. The chapter's novel proposal is established to consider all scenarios, mainly involving extreme wind, frozen precipitation, fog, liquid precipitation, fiood along with high and low temperatures. These risk groups are analysed and ranked. With regard to intermediate nodes, I2 (obstruction), I3 (slipping) and I5 (trackbed problems) are identified as the most influential risk groups to derailments. Quantitively, obstruction has a 61 responsibility for derailments, which is found to be quite higher than trackbed problems and slipping combined. As for root nodes, R2 (frozen precipitation) is identified to be the major cause to derailments, accounting for 49% among all root nodes.

Chapter 4 also identifies why railway operators need to apply maintenance strategy on the basis of climate regions. This is essential as temperature and precipitation have strong impact on derailments. In the light of these findings, the methodologies of Chapter 6 and Chapter 7 are designed in accordance with regional segmentation based on temperature and precipitation

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CHAPTER 5

BAYESIAN NETWORK-BASED HUMAN ERROR PROBABILITY ASSESSMENT OF DERAILMENTS AT SWITCHES AND CROSSINGS

5.1 Introduction

The preceding chapter has been designed to examine environmental causes in the analysis of accidents connected with railway turnouts. This chapter is prepared to reveal and analysis human errors by utilising from a novel methodology that is proposed by the thesis.

The knowledge gained from component-related failures has contributed considerably to the design of a more reliable component, lessening railway accidents attributable to various system malfunctions. These new designs have led to novel changes in railway operations and technologies. Therefore, railway employees now find themselves in a more complex and esoteric environment. The opportunities for failure that involve human (i.e. dispatchers, train crews and roadway workers) interactions have become one of the safety barriers.

The safety of railway operations heavily depends on several factors, including the quality of railway organisation, railway traffic rules, reliability of rolling stock and infrastructure and human factors. Recent studies have revealed that in Europe, at least one-fourth of fatal railway accidents over the last two decades have resulted from various human errors, such as signal passed at danger, exceeded speed, communication problems, signalling or dispatching error (Dindar et al., 2018a, Evans, 2011). The consequences of such human failures in the railway industry, on the other hand, were illustrated to result in severe or catastrophic derailments, which often results in operation shutdown, damages to railway infrastructures, injuries or even human losses (Kyriakidis et al., 2015).

Aside from the railway enterprise, the risk identification and management of human errors are also quite complex and, in many ways, distinct from other forms of risk analysis techniques applied to other engineering areas such as component failures (Dindar et al., 2018b). Differences found between risk analysis of human research and different kinds are arguably more profound in gathering linguistic data by industrial experts than in dealing with statistical overviews by accident reports. As a result, a significant proportion of data analysis in this study is given over to a mathematical analysis of linguistic context.

To achieve to thesis objectives [1] (aiming at analysing human errors) and investigates the allocated task related to human errors, this chapter attempts to follow a phased approach: (1) summarise impact of different kind of switches and crossings on human errors; develop a unique methodology to handle complexity of risk analysis; (2) underline the generic theory to readers and illustrate how to implement fuzzy Bayesian networks and fuzzy set theory into human error probability of derailments; (3) reveal, as a result of data processing, unique human errors giving rise to derailment at turnouts; determine risk nodes and assign them in a unique causal Bayesian network; (4) show the findings arisen from a stochastic process; and eventually (5), interpret and describe the significance of the findings providing a number of suggestions that will allow the railway industry to remedy the human errors, and underline any new insights about the research problem.

[1] As expressed in Chapter 1.5,

- The identification of risk prioritisation of turnouts in various operational environments
- The development of a concise and intuitive visualisation of a framework
- The identification of an appropriate risk analysis method to railway turnouts

5.2 Method

5.2.1 Structure of methodology

The methodology of this chapter is established on four fundamental phases, exhibited in Figure 5.1, each of which is addressed to a discussion of the underlying reasoning why particular methods were used to gather the ultimate understanding of human errors resulting in derailments with any consequences at switches and crossings. The details of the phases are given briefly as follows:

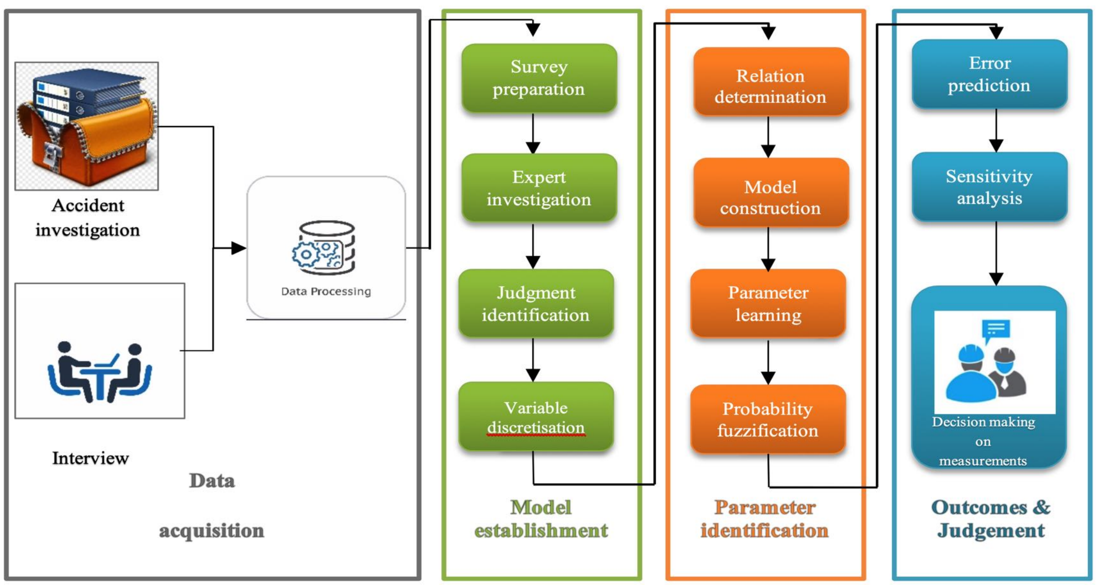


Figure 5.1: Presentation of techniques used in methodology

Since there is a lack of knowledge of essential human errors related to turnouts exist in literature, this study has attempted to do a two steps of data investigation, namely data gathering and data processing.

Data gathering involves official accident record and interviews. As accident reports of Turkish Railway Agency (TCCD) are not published and have no access to public, full access is given to the researchers being restricted to acquiring information about other kinds of railway accidents, i.e. collision, and other railway infrastructures, i.e. plain rail lane.

Interviews with railway experts having at least twenty years experience are performed to justify whether or not data is incomplete, or some values are not missing. These interviews were conducted through a semi-structured format, meaning that the main issues are encouraged to emerge from the interviewees, rather than being imposed by the structure of the interview (see Appendix B). The distribution of their occupations is intended to be wide since more in-depth qualitative exploration of the perspectives of individuals with different backgrounds is needed. The overview of occupation distribution is illustrated in the bar chart on left-hand side of Figure 5.2.

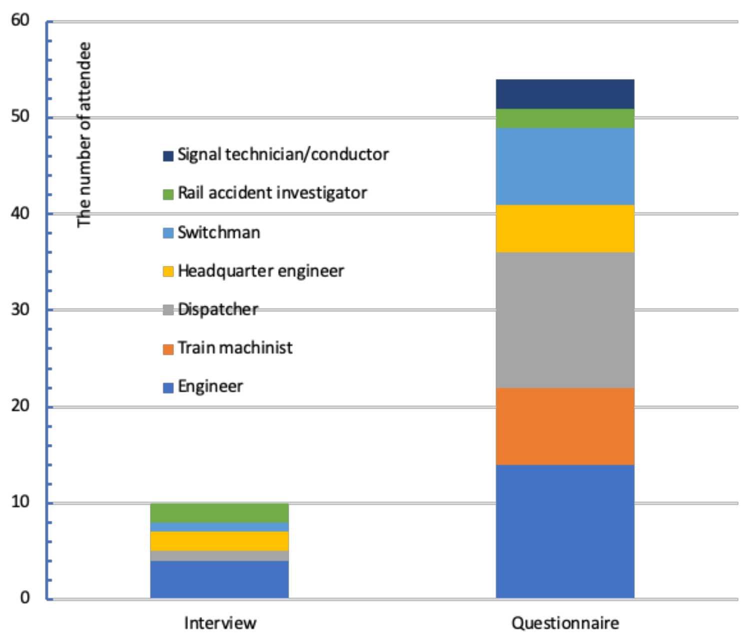


Figure 5.2: The number of attendees by occupation

Ten railway industry experts are contacted to obtain overall knowledge which enables this study to not only prepare a proper questionnaire (see Appendix B1.2), but also observe the inception of their rail disciplines for eliciting a more detailed or ‘in-depth’ understanding of the relations between risk groups, such as communication or signalling errors. When the quality and richness of the interview data are considered to allow for the establishment of questionnaire, the interview records are used to build up over 70 multiple choice questions. The same ten experts, afterwards, are asked to make a comment on the robustness of the questions, and where a revision necessitates, fundamental changes have been made.

Railway experts in the sample group responding to the questionnaire are different from ones interweaved before (see Appendix B.1.3). Both groups are composed of a wide range of demographic variables, including railway engineers (mostly mechanical engineer and civil engineer), switchman, dispatcher, railway accident investigators (mostly statisticians), train mechanist, headquarter engineer (mostly senior engineers with different background), signal technician and conductors. Phases 2, 3 and 4 are underlined and discussed in the following sections.

To enhance the quality of data gathered from interviews, a pre-session has been arranged for fifteen potential experts, and the number of interviewees has been reduced down to ten, allowing to prepare a detailed questionnaire. The selection of interviewees has been carried out by considering a restriction for experience regarding turnout-related accidents, i.e., selecting only experts who have been involved in conducting a reasonable number of accident reports or investigations, and for whom the given opinion is unlikely to have had an effect on their occupations in the Turkish railway agency.

5.2.2 Understanding human Error in turnout operation

5.2.2.1 Types of Human Error

Different types of human error have been distinguished in terms of the causes of those errors in many research studies (Meister, 1971, Thomas et al., 2002, Woodson et al., 1992). These classifications that are covered in this study are established throughout the following groups:

Design-induced errors take place in railway accidents as a result of human incompatibilities with the design of turnouts or its operational design. Numerous difficulties for railway operators, i.e. loco machinist, dispatcher, might be created by equipment design characteristics or design errors in turnouts and in signal operation.

Human-induced errors are characteristics of railway workers that influence the potential for errors. The common characteristics might be fatigue, distraction, disorientation, excessive stress, lack of motivation, impaired attention, forgetting any task, inadequate skills and knowledge, confusion, complacency, incorrect expectancy, use of drugs and inadequate or impaired perceptual or cognitive ability.

System-induced errors reflect human-based deficiencies in the way a railway management system is implemented. It is considered that this group of human errors includes various mistakes in designating the types or numbers of railway personnel, in training organisation, in maintenance requirements for turnout and in communication.

5.2.2.2 Identification of Human Factors

The absolute number of overall hazardous events in the railway industry around the world tends to decrease. However, the causal factors that contribute to unsafe events have so far been observed to increase. The percentage of reportable incidents and accidents attributable to human factors increased by about 12 percent in the US over the last few decades (Wreathall et al., 2007)[2]. Although the culmination of a sequence of events, and a variety of circumstances or conditions are frequently attributed to train derailments, human factors alone seem to be ample to result in derailments. Physical condition, omission, act or several other reactions of a railway employee are alleged as the primary cause of a railway accident/incident. Thus, the human causes must be categorised in the following groups:

Use of Brake

Where a type of train protection system[3] (PTC) is neither available nor in use for some reason, failures in brake of use have often been observed to take place as primary cause. The total human errors are illustrated in Table 5.1. Locomotives equipped with loco driver brakes[4] to control the speed often fall into the responsibility of loco drivers. Some rare events particularly in rural areas, non-railway employees (A7) are observed to be involved in derailments. While a train siding[5] takes place on the railway line, hand brakes of locomotive (A5) or, where possible, wagons (A6), are required to prevent undesired movement. Otherwise, a locked pair of switch blades on exit or entrance of a siding lead a sliding train to run off its rails. A sufficient number of hand brakes, on the other

[2]As Turkish railway agency wants the authors to not use official reported numbers in this research, the US is given an example. However, it can be stressed herein that the similar trend is observed in Turkey along with other many European countries. See: `https://ec.europa.eu/eurostat/statistics-explained/index.php/Rail_accident_fatalities_in_the_EU`

[3]An advanced railway safety system designed to automatically lessen the speed of train or stop before certain accidents occur, and thereby to prevent derailments caused by excessive train speed, train movements through misaligned track switches, unauthorized train entry into work zones and train.

[4]A loco driver is referred to a railway employee who can drive and stop a train in cab, and let the brakeman or conductor dismount, and throw switch blades to the correct position.

[5]An additional short stretch of railway track used to enable trains on the same line to pass or store rolling stock.

hand, should be applied by a loco driver to ensure safe passage on a particular long railway turnout (A2). As a result of failure to apply hand brakes on wagon(s) (A1) or failure to release hand brakes on wagon(s) (A3) by any railway employee, insufficient braking forces allow the train to increase speed, where a slope exists in trailing direction, or to remain out of speed allowance.

Table 5.1: Human errors associated with the use of brake.

Node	Description	Type of human error
A1	Failure to apply hand brakes on wagon(s) (railway employee)	Human-induced errors
A2	Failure to apply sufficient number of hand brakes on wagon(s) (railway employee)	Human-induced errors
A3	Failure to release hand brakes on wagon(s) (railway employee)	Human-induced errors
A4	Failure to control speed of wagon using hand brake (railway employee)	Human-induced errors
A5	Failure to properly secure loco(s) (railway employee)	Human-induced errors
A6	Failure to properly secure wagon(s) (railway employee)	Human-induced errors
A7	Failure to properly secure engine(s) or wagon(s) (non-railway employee)	Human-induced errors

Train handling

Locomotive drivers are obligated to exercise judgment and planning to operate their train safely and efficiently. The responsibility for controlling the slack in the train is given to the engineer. The desired train handling necessitates the proper combination of actions given in Table 5.2.

Employee physical condition

Railway employees often encounter occupational health and safety (OHS) risks due to the reasons illustrated in Table 5.3. The majority of interviewees have underlined a consider step dealing with OHS risks cannot somehow be taken yet even though there is growing acknowledgement and awareness of a wider and more di-

Table 5.2: Human errors associated with Train Handling.

Node	Description	Type of human error
B1	Automatic brake, excessive	Human-induced errors
B2	Automatic brake, failure to use split reduction	Human-induced errors
B3	Automatic brake, insufficient	Human-induced errors
B4	Slack action excessive, train handling	Human-induced errors
B5	Dynamic brake, excessive	Human-induced errors
B6	Dynamic brake, excessive axles	Human-induced errors
B7	Dynamic brake, insufficient	Human-induced errors
B8	Dynamic brake, other improper use	Human-induced errors
B9	Dynamic brake, too rapid adjustment	Human-induced errors
B10	Failure to allow air brakes to fully release before proceeding	Human-induced errors
B11	Failure to properly cut-in brake valves on locomotives	Human-induced errors
B12	Failure to properly cut-out brake valves on locomotives	Human-induced errors
B13	Failure to properly cut-out brake valves on locomotives	Human-induced errors
B14	Improper placement of wagons on train between the terminal	Human-induced errors
B15	Lateral drawbar force on curve excessive, wagon geometry (short wagon/long wagon combination)	Human-induced errors
B16	Lateral drawbar force on curve excessive, train handling	Human-induced errors

verse set of OHS risk factors confronted by the employees. Aside from Turkey, the rest of Europe struggles with finding a proper solution regarding the serious deterioration of both mental and physical health of railway employees. About one-fifth of people employed in the EU-27 reported experiencing anxiety, depression or stress, and the data is observed to be stable for a long time (Marczak and Hassard, 2016). Railway turnouts require a special focus due to the nature of their vulnerable operation. Consequently, human error(s) could be a result of a combination of C1, C2, C3 and C4 that lead to anxiety, depression or stress.

The majority of them are identified as system-induced errors, due to the fact that they (C1, C2, C3) might take place as a result of a deficiency in human management systems, conducted by railway headquarters. Common mistakes include (1) railway employees are not consulted on shift patterns and working hours, (2) changes to working hours are not assessed, (3) lack of a properly developed policy that specifically addresses and sets limits on working hours, shift-swapping and overtime in order to guard against employee fatigue.

Table 5.3: Human errors associated with employee physical condition.

Node	Description	Type of human error
C1	Employee asleep	System-induced errors
C2	Employee restricted in work or motion	System-induced errors
C3	Impairment of efficiency or judgment because of drugs or alcohol	Human-induced errors
C4	Incapacitation due to injury or illness	System-induced errors

Control systems

The most used train control systems are Cab signal and Automatic train protection system (ATP). Cab signal is a visual signal in the cab of a locomotive ,which provides a continuous indication of the state of the track ahead or a continuous reminder of the last wayside signal for locomotive drivers. The majority of trains have been updated with the automatic cab signal system in Turkey. Automatic Train Control, providing full automation of train control by means of the prediction of braking & acceleration, and illustration of switch position, is also in operation in Turkey. Possible explanations for any human errors associated with control systems and involving a derailment are illustrated in Table 5.4. Not only are the two reasons directly responsible for derailments, but they might act as a contributory factor. For instance, any kind of safety control system that automatically prevents trains from speeding might be enforced by a loco driver to not be in service. In such cases, train control systems take a contributory act to over-speed (as primary factor) leading to a train running away off turnouts.

Table 5.4: Human errors associated with control systems

Node	Description	Type of human error
D1	Control system signal cut out	Human-induced errors
D2	Control system, failure to comply	Human-induced errors

Speed

Travel through the diverging route of a turnout tends to generate accelerations and high lateral forces, mostly on a switch point and a crossing nose. As a result, the design of a turnout enables diverging speeds to be assigned by considering its unique peak lateral accelerations and wheel/rail interaction. Where any control system is not available or somehow in use, excessive speed (E1, shown in Table 5.5) is likely to take place in switch operation. On the other hand, the indication of signal governing train movement from a turnout to another, or siding to the main track, could not meet the engineering criteria of a turnout.

Table 5.5: Human errors associated with speed

Node	Description	Type of human error
E1	Switching movement, excessive speed	Human-induced errors
E2	Failure to engineer design of restricted speed	Design-induced errors

Flagging, Fixed, Hand and Radio Signals

Railway Employees who display or give signals are obligated to have the proper appliances. The responsibility of the appliances being in good condition and ready to use (F8 and F11) belongs to the user. To ensure recognition and following signal rules correctly, railway employees are required to comply with the intent of the signal (F1, F5 and F9), not to act on any signal that may be intended for other trains or that they do not understand (F3). To give clear signals during the day and at night, railway employees are obligated to use the required colour of lights or flags during the day and use the required colour of reflective lights or flags (F7 and F8). In addition to this, signals should be plainly seen, and be clearly given so that they can be understood by a loco driver. To achieve proper movements of rolling stock, radio communication might take place in railway operation. Railway employees are required to meet specific instructions given for each movement (F10). On the other hand, dispatchers and loco drivers must make sure which moves will be made by radio communication (F11 and F12).

Use of Switches

Table 5.6: Human errors associated with Flagging, Fixed, Hand and Radio Signals

Node	Description	Type of human error
F1	Automatic block or interlocking signal displaying a stop indication – failure to comply	Human-induced errors
F2	Blue Signal, absence of	Design-induced errors
F3	Improper signal location	Design-induced errors
F4	Any signs covered by obstacles or damaged signs	System-induced errors
F5	Failure to comply with failed equipment detector warning or with applicable train inspection rules	Human-induced errors
F6	Failure to observe hand signals given during a wayside inspection of moving train	Human-induced errors
F7	Fixed signal (other than automatic block or interlocking signal), failure to comply	Human-induced errors
F8	Flagging signal, failure to comply	Human-induced errors
F9	Flagging, improper or failure to flag	Human-induced errors
F10	Hand signal improperg	Human-induced errors
F11	Radio communication, failure to comply	Human-induced errors
F12	Automatic brake, failure to use split reduction	Human-induced errors
F13	Radio communication, failure to give/receive	Human-induced errors
F14	Radio communication, improper	Human-induced errors

A switch, often even if it is an automatic switch, could be operated by hand. Three different kinds of switch operations are considered and grouped; namely, hand-operated, spring switch and radio controlled, as seen in Table 5.7. Switches operated by hand are called hand-operated switches. The crew member must stop the train and make sure that (1) hand-operated switches are properly aligned for the intended route (G1); (2) the points of turnout should fit properly and the target, if so equipped, corresponds with the switch's position (G1); (3) after locking a switch or derail, a crew member should test whether or not the lock is secured (G1); and (4) where the operating lever is equipped with a latch, the latch should not be stepped on to release the lever except for when throwing the switch (G5), which a maintenance team is responsible for. Spring switches should be operated through following human oriented rules: (1) A train must be stopped while a facing point movement over a spring switch is performed, and a crew member must test the switch (G2); (2) a train must be stopped, and the slack is controlled while trailing through and stopping on a spring switch (G2); (3) a train, approaching a spring switch in non-signalled territory, must pass throughout the facing points of a spring switch prepared to stop till a distant signal displays clear or the switch is indicated to be properly lined (G2). To operate a radio-controlled (automatic) switch, a crew member is obligated to ensure the following: (1) siding operation cannot be performed when the train is not stopped before passing the overlap sign, even indicating proceeding (G3 and G4); (2) a train entering the main track must move past the overlap sign, and when a proceed indication by the signal governing movement over the switch is enabled for further movement (G3 and G4). Loco drivers are enforced to not run through switches except spring switches (G6). If switch run-through takes place, the train must continue movement over the switch (G6).

Table 5.7: Human errors associated with use of switch

Node	Description	Type of human error
G1	Moveable point, switch, crossing nose improperly lined, hand-operated	Human-induced errors
G2	Spring switch not cleared before reversing	Human-induced errors
G3	Radio-controlled switch not locked effectively	Human-induced errors
G4	Switch improperly aligned, radio controlled	Human-induced errors
G5	Switch not latched	System-induced errors
G6	Switch previously run through	Human-induced errors

5.2.3 Fuzzy Bayesian networks and fuzzy set theory

To deal with uncertainty stemmed from the imprecision and vagueness, fuzzy set theory (FST) is used for this study. FST provides a basis to generate powerful problem-solving techniques with wide applicability, especially in the field of decision making. Fuzzy numbers, which are an extension of real numbers, have their own properties associated with the theory of numbers.

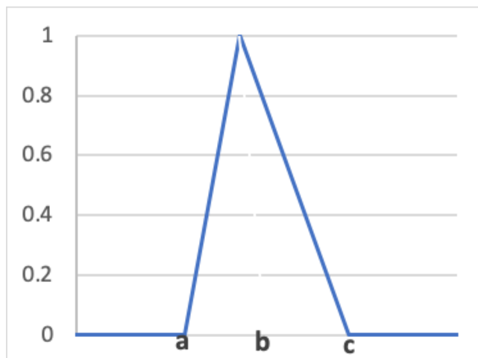
Definition 1: Let E and A be a Fuzzy Subset and a set contained in E, respectively. Then, $(x, \mu_A(x))$ refers to the fuzzy subset A of E, where $\mu_A(x)$ is the degree of membership of x in E, and x is a single element E.

Definition 2: A membership function for a fuzzy set A is expressed as $\mu_A : X \rightarrow [0, 1]$, where each element of X is mapped to a value between 0 and 1.

Definition 3: *A* Fuzzy Number ($\tilde{A} = (a, b, c)$) is called a triangular fuzzy number if its membership function is given by

$$\mu_A(x) = \begin{Bmatrix} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & x = b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c < x \end{Bmatrix}$$

Where a, b and c can be arbitarily plotted on a two-dimension graph as follows:



The number of attendees by occupation

Definition 4: The operators between two fuzzy sets are defined as follows:

$$\begin{cases} \widetilde{A}_1 \oplus \widetilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \\ \widetilde{A}_1 \ominus \widetilde{A}_2 = (a_1 - a_2, b_1 - b_2, c_1 - c_2) \\ \widetilde{A}_1 \otimes \widetilde{A}_2 = (a_1 a_2, b_1 b_2, c_1 c_2) \\ \widetilde{A}_1 \oslash \widetilde{A}_2 = \left(\frac{a_1}{a_2}, \frac{b_1}{b_2}, \frac{c_1}{c_2}\right) \end{cases}$$

5.2.4 Integration of expert review into fuzzy sets

Reliability levelling

Since experts are often invoked when quantities of interest are uncertain, a defensible quantification of uncertainty, thereby, is required to be established. This study proposes an expert confidence indicator (ECI) to judge the reliability of the data obtained from surveys with experts. With regard to ECI, the reliability of expert opinions is conducted through the following equation:

$$\omega = \gamma.\zeta \tag{5.1}$$

where γ and ζ denote the occupation and experience, respectively, of the railway employee. Those are proposed to be measured by Table 5.8 and Table 5.9.

Table 5.8: Subjectivity reliability levels

Levels	Definition	γ
1	Railway accident investigator	1.0
2	Field supervisor	0.9
3	Engineer (at headquarter)	0.9
4	Train dispatcher chief	0.8
5	Train dispatcher	0.7
6	Train machinist / Switchman	0.7
7	Signal technician/Conductor	0.5

Table 5.9: Expert experience levels

Levels	Definition	ζ
1	Railway accident investigator	1.0
2	Field supervisor	0.9
3	Engineer (at headquarter)	0.8
4	Train dispatcher chief	0.6
5	Train dispatcher	0.4

Linguistic variables

The ineffectiveness of probability calculation in carrying out humanistic systems might be argued to be a manifestation of what is called the principle of incompatibility [6] (Zadeh, 1975). Therefore, it might be suggested that, in order

[6] It asserts that high precession is incompatible with high complexity.

to analyse an appropriate risk in research-based human behaviour systems, the high level of preciseness of any mechanical system might be abandoned. In coping with the overpowering complexity of an intended system, it is a scientifically natural approach to use linguistic variables.

Linguistic variables provide concrete insight to analysis properly human knowledge representation. The variables are generated from an artificial language or words or sentences, and as a natural consequence, are less specific than numbers. On the other hand, the variables can be represented through membership functions that fit into what has been achieved mathematically in the Fuzzy theory section of this paper.

Table 5.10 is contructed to divide likelihoods of nodes, which correspond to the questions asked to railway employees, by twelve equals intervals. Then each likelihood responds to a fuzzy domain with a unique lower boundary (a_i) and a unique upper boundary (a_{i+1}). The first column of the Table 5.10 illustrates linguistic labels of events, while the other columns express fuzzy definition of given linguistic labels. Considering the subjective nature of the language used to describe probability, the probability intervals are given to railway employees before the questionnaire and interview so that comprehension of the chances of events is provided properly.

Thus, reliability level and experience level are modelled and nested into the lower and upper boundaries throughout the following equation;

$$\widetilde{A_n} = \begin{cases} \frac{(a_i - a_{i-n})}{\sum_{j=0}^{i-1}(a_i - a_j)} \times \frac{1-\omega}{2}, & 1 \leq n < i-1 \\ \frac{(a_{61-i+n} - a_i)}{\sum_{j=i+1}^{10}(a_j - a_i)} \times \frac{1-\omega}{2}, & i+1 \leq n < 10 \end{cases}$$

Table 5.10: Divisions of occurrence probability intervals

Linguistic labels	Probability intervals(i), $((a_i), (a_{i+1})]$ Lower boundary (a_i)	Upper boundary (a_{i+1})	Mean of interval (μ_i)
Impossible	0.00	0.00	0.00
Almost impossible	0.00	0.05	0.25
Quite unlikely	0.05	0.15	0.075
Unlikely	0.15	0.25	0.15
Improbable	0.25	0.35	0.25
Possible	0.35	0.45	0.35
Even chance	0.45	0.55	0.45
Better than even	0.55	0.65	0.55
Likely	0.65	0.75	0.65
Quite likely	0.75	0.85	0.75
Highly probable	0.85	0.95	0.85
Almost certain	0.95	1.00	0.925
Certain	1.00	1.00	0.975

5.2.5 Establishment of noisy-Or Bayesian network

5.2.5.1 Causal Independence

A standard BN is used to compute the probabilities of the presence of several variables mostly in the presence of a causal independence. The network represents a set of variables and their conditional dependencies throughout a directed acyclic graph (DAG) (probabilistic graphical model). As seen in Figure 5.3, considering hierarchical levels of the network, nodes higher than a given node in the same lineage are parents, and the given node, in turn, is the child's parent. Bayesian networks do not often place any restrictions on how a child node is assigned to its parent(s). Thus, nodes are labelled with random variable(s) in the following way.

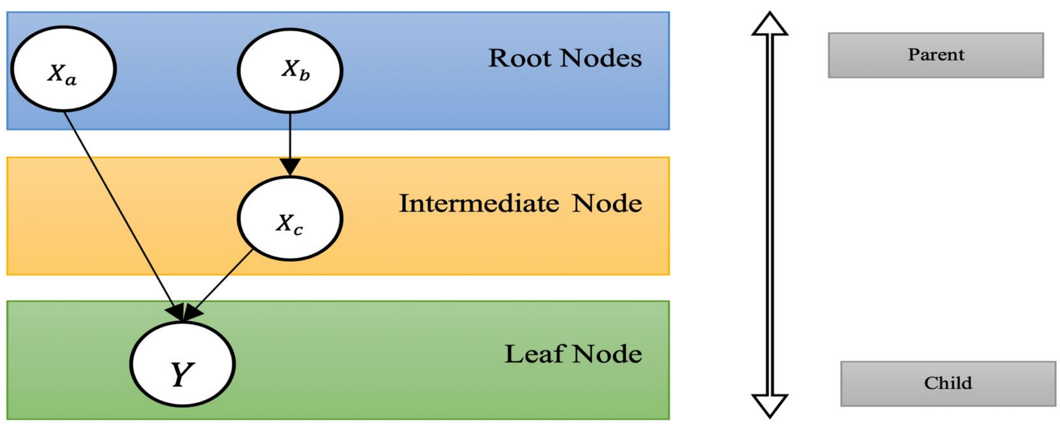


Figure 5.3: Directed acyclic graph (DAG) representing two independent roots and an intermediate node causing an evidence (leaf node)

Let's say, X_a and X_b are two independent potential causes (root nodes) of Y, as shown in the Figure 5.3. X_c is determined as an intermediate node of the network. The overall goal is to compute the posterior conditional probability distribution (PCPD) of each of these independent causes given a new evidence (leaf node) takes place, i.e. $P(X_a|Y)$. To do this, the conditional independence assertions and the conditional probabilities together of these two independent potential causes and the intermediate node entail a joint probability over Y. By the chain rule,

$$P\left(Y, X_a, X_b, X_c\right) = P(Y)P\left(X_a\right)P\left(Y|X_a, X_b\right)P\left(X_b\right)P\left(X_c|X_b\right) \tag{5.2}$$

where $P\left(X_a\right)$ and $P\left(X_b\right)$ denote marginal probabilities of the given network. Conditional probabilities of causal relationships are expressed through $P\left(Y|X_a, X_b\right)$ and $P\left(X_c|X_b,\right)$ both of whose derivations are illustrated in Table 5.11 and Table 5.12 respectively.

Table 5.11: Conditional Probability of $\mathrm{P}\left(\mathrm{X_c}|\mathrm{X_b},\right)$

X_b	$P\left(\left(X_c = x_{c_1}\right)|X_a\right)$	$P\left(\left(X_c = x_{c_2}\right)|X_a, X_b\right)$
x_{b_1}	$\frac{p_{x_{b_1}, x_{c_1}}}{p_{x_{b_1}}}$	$\frac{p_{x_{b_1}, x_{c_2}}}{p_{x_{b_1}}}$
x_{b_2}	$\frac{p_{x_{b_2}, x_{c_1}}}{p_{x_{b_2}}}$	$\frac{p_{x_{b_2}, x_{c_2}}}{p_{x_{b_2}}}$

Table 5.12: Conditional Probability of $\mathrm{P}\left(\mathrm{Y}|\mathrm{X_a}, \mathrm{X_b}\right)$.

X_b	X_b	$P\left(\left(X_c = x_{c_1}\right)|X_a\right)$	$P\left(\left(X_c = x_{c_2}\right)|X_a, X_b\right)$
x_{a_1}	x_{b_1}	$\frac{p_{x_{a_1}, x_{b_1}, y_1}}{p_{x_{a_1}, x_{b_1}}}$	$\frac{p_{x_1, x_{b_2}, y_2}}{p_{x_{a_1}, x_{b_2}}}$
x_{a_1}	x_{b_2}	$\frac{p_{x_{a_1}, x_{b_1}, y_1}}{p_{x_{a_1}, x_{b_1}}}$	$\frac{p_{x_{a_1}, x_{b_2}, y_2}}{p_{x_1, x_{b_2}}}$
x_{a_2}	x_{b_1}	$\frac{p_{x_{a_2}, x_{b_1}, y_1}}{p_{x_{a_2}, x_{b_1}}}$	$\frac{p_{x_{a_2}, x_{b_2}, y_2}}{p_{x_{a_2}, x_{b_2}}}$
x_{a_2}	x_{b_2}	$\frac{p_{x_{a_2}, x_{b_1}, y_1}}{p_{x_{a_2}, x_{b_1}}}$	$\frac{p_{, x_{a_2}, x_{b_2}, y_2}}{p_{x_{a_2}, x_{b_2}}}$

True, i.e. $P\left(\left(x_c = x_{c_1}\right)|x_a\right)$, and false, i.e. $P\left(\left(X_c = x_{c_2}\right)|X_a, X_b\right)$, conditional probabilities along with their statistical expressions are presented. As noted, a node in the network is assigned a particular set of values as input for its parent variables and given the probability (as output) of the variable represented by the node. In other words, a node with n parent(s) constitutes n Boolean variables, which means that a table of 2^n entries should exist to perform the joint probability of the node. Thus, excessive burden of calculation is required in a network with a large number of causal relationships. As the research has been modelled by dealing with over 60 nodes, a standard BN model would need over 100,000 inputs, which makes the research ineligible to be conducted. As a result, a canonical-based distribution, namely Noisy-Or method, is applied to the study.

5.2.5.2 Noisy-OR gate

The Noisy-OR model is a generalized version of the logical *OR* gate, and it is established by assuming that there is a disjunctive causal interaction among child, parent, and/or leaf node(s), rather than a conjunctive causal interaction. This interpretation is often associated with a cause and effect model where the child node is assigned as an event sufficient to impact each parent node. In contrast to standard BN considering every parent-state combination, the Noisy-OR based BN model, therefore, entails only that a node be parameterized for the cases where a single parent event takes place. To be more specific, two assumptions are made by the Noisy-OR model. (1) Each of the causes (X_i), (whether it is root or intermediate node) a probability of p_i, which is quite enough to absence of other causes. (2) The ability of each cause, which is quite enough, is independent of the presence of other causes in the network. These two assumptions enable identifying the entire conditional probability distribution with only n parameters $(p_a, \ldots, p_n)$, representing the probability effecting child nodes. Providing that only one of the causes (parents) exists in the network, the child takes place by the following equation.

$$p_i = P\left(y|x_a, x_b, \ldots, x_n\right) \tag{5.3}$$

Thus, the probability of y given a subset X_p of X_i s is calculated by the equation below.

$$P\left(y|X_p\right) = 1 - \prod_{i:X_i \in X_p} \left(1 - p_i\right) \tag{5.4}$$

The conditional probabilities (p_i) of nodes are given in the specification of the Bayesian network. Eventually, arbitrary probabilistic reasoning in a network is achieved. For instance, the given probabilities by Table 5.12 are rearranged through Eq. 5.3 in Table 5.13.

Table 5.13: Rearrangement of a conditional probability.

X_b	X_b	$P\left(\left(Y=y_1\right)\lvert X_a, X_b\right)$	$P\left(\left(Y=y_2\right)\lvert X_a, X_b\right)$
x_{a_1}	x_{b_1}	$1-\frac{p_{x_{a_1},x_{b_1},y_1}}{p_{x_{a_1},x_{b_1}}} \times \frac{p_{x_{a_2},x_{b_2},y_2}}{p_{x_{a_2},x_{b_2}}}$	$\frac{p_{x_{a_1},x_{b_2},y_2}}{p_{x_{a_1},x_{b_2}}} \times \frac{p_{x_{a_2},x_{b_2},y_2}}{p_{x_{a_2},x_{b_2}}}$
x_{a_1}	x_{b_2}	$1-\frac{p_{x_{a_1},x_{b_1},y_1}}{p_{x_{a_1},x_{b_1}}}$	$\frac{p_{x_{a_1},x_{b_2},y_2}}{p_{x_{a_1},x_{b_2}}}$
x_{a_2}	x_{b_1}	$1-\frac{p_{x_{a_2},x_{b_1},y_1}}{p_{x_{a_2},x_{b_1}}}$	$\frac{p_{x_{a_2},x_{b_2},y_2}}{p_{x_{a_2},x_{b_2}}}$
x_{a_2}	x_{b_2}	0	1

As seen, the Noisy-OR parameterization allows the original 4 parameters of CPT to be decreased to 2 parameters. In other words, in contrast to the standard BN model which requires 2^n entries, the number of CPT entries is 2n in the Noisy-OR model. Therefore, it is said that this technique will enable dealing with a large number of nodes as the number of CPT parameters associate with a linear function with Noisy-OR rather than an exponential increase.

5.2.5.3 Integration of the nodes in a Bayesian network

A BN is technically a graphical model that displays nodes (also referred to as variables), their conditions and independencies. Therefore, causal relationships between nodes, which generally illustrates cause and effect, are established through the links in the network (also known as arcs). As revealed in Chapter

5.2.2, the BN that handles risk distribution and causal relationships between various human errors leading to a derailment at turnouts is revealed to include 51 intermediate nodes and 1 leaf node. So, the probabilistic independencies between the nodes as displayed on the graph first required to be identified. As a result of interviews, Table 5.14 exhibits the one-way-relations of the nodes. Relationships between nodes are made through Boolean data as this is the most straightforward way to represent the two truth values of logic. Two possible values; virtually 1, 0, are assigned as shown in Table 5.14. It is brought out that employee physical conditions (employee asleep (C1), employee restricted in work or motion (C2), impairment of efficiency or judgment because of drugs or alcohol (C3), incapacitation due to injury or illness (C4)), aside from its primary impact, often lead to a contributory impact on the other human-error nodes. On the other hand, some nodes are observed to be linked only to a group, such as control system failures. It is also worth noting that Table 5.13 disregards nodes without any link to intermediate nodes to facilitate the visualisation and understanding of the significant fundamental relations throughout the BN.

Considering Table 5.14 and the relationship between some intermediate nodes (A, B, C, D, E, F, G) and a leaf node (Y; namely, derailment), Figure 5.4 is prepared to provide a visual representation of the concealed structure of joint probability distributions. In other words, the structure reveals human error-based derailment causes at turnouts by encoding raw information about the conditional independence relationships among all random variables. As seen in Figure 5.4, a set of intermediate nodes (A, B, C, D, E, F, G) is added to the DAG structure. Each is associated with a subset of failure nodes and named through a unique prefix of these failure codes. For instance, Node A, coloured as yellow hollow hoop in the structure, refers to human errors in the brake of use (see 5.2.2.2), which encapsulates node names A1 to A7 (see Table 5.1).

Table 5.14: Causal relationships between nodes

Child Nodes	Parent Nodes															
	C1	C2	C3	C4	D1	D2	F1	F2	F3	F4	F6	F10	F11	F12	F13	F14
A1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A2	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0
A3	1	1	1	1	0	1	1	1	0	0	1	1	1	1	1	0
A4	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0
A5	1	1	1	1	0	0	0	0	0	0	1	1	0	1	1	1
A6	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1
A7	1	1	1	1	0	0	0	0	0	0	1	1	0	1	1	1
B1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B3	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B5	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B6	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B7	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B8	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B9	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B10	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B11	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B12	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B13	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B14	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B15	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B16	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
D1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
D2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
E1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1
E2	0	0	0	0	1	1	0	1	1	0	0	0	0	1	1	1
F1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5.14 *(Continued)*.

Child Nodes	Parent Nodes															
	C1	C2	C3	C4	D1	D2	F1	F2	F3	F4	F6	F10	F11	F12	F13	F14
F3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F5	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F6	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F7	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F8	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F9	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F10	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F11	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F12	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F13	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F14	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0

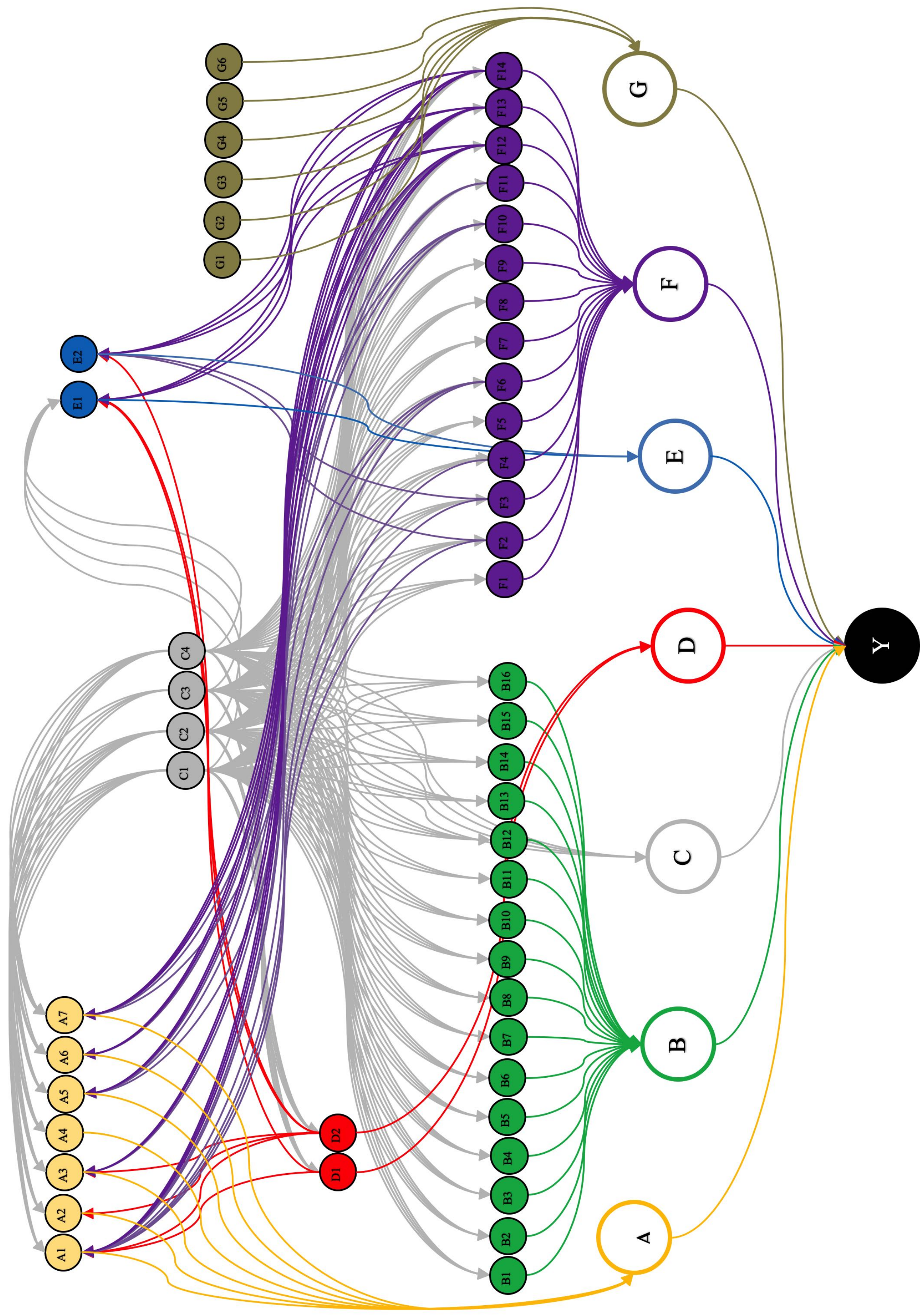


Figure 5.4: DAG establishment of human error-based derailment causes at turnouts (HEDC)

5.3 Results

5.3.1 Execution of marginal and conditional probability distributions

The proposed DAG is composed of 59 unique nodes, each of which responds to various human behaviour errors which might result in derailments at railway turnouts. As discussed in section 5.2.5., the main reason for the choice of such a comprehensive methodology built-in a Noisy-OR approach is that data is provided by railway employees with different background and occupations. For instance, Node B (human errors associated with Train Handling) is of 16 parent-nodes (B1 to 16). Therefore, they would be asked $65,536\,(2^{16})$ times to reach the conditional table of the node.

Instead of such an impossible reviewing event, a unique Noisy-OR data gathering process (see Sec.6 has been developed and integrated into modified equations in 5.2.5. This process enables the preparation of CPD tables. In this study, over 200,000 CPD executions were performed through a comprehensive MATLAB-based programme developed specifically for this research.

Figure 5.5 illustrates measures of all probabilities of the event 'D1' given that either one of the parents (or more) in the DAG or another event that is not presented in the DAG has occurred. As seen in Table 5.13, C1, C2, C3 and C4 are assigned as parents of the D1. In other words, the sample space of 2^4 combinations are distributed in a way that each probability computation between D1 and the others ($\mu_A(x)$) is represented. As the methodology of exaction includes leaky Noisy-Or Structure, $P\left(D1_T|C1_F, C2_F, C3_F, C4_F\right)$ is quite higher that the

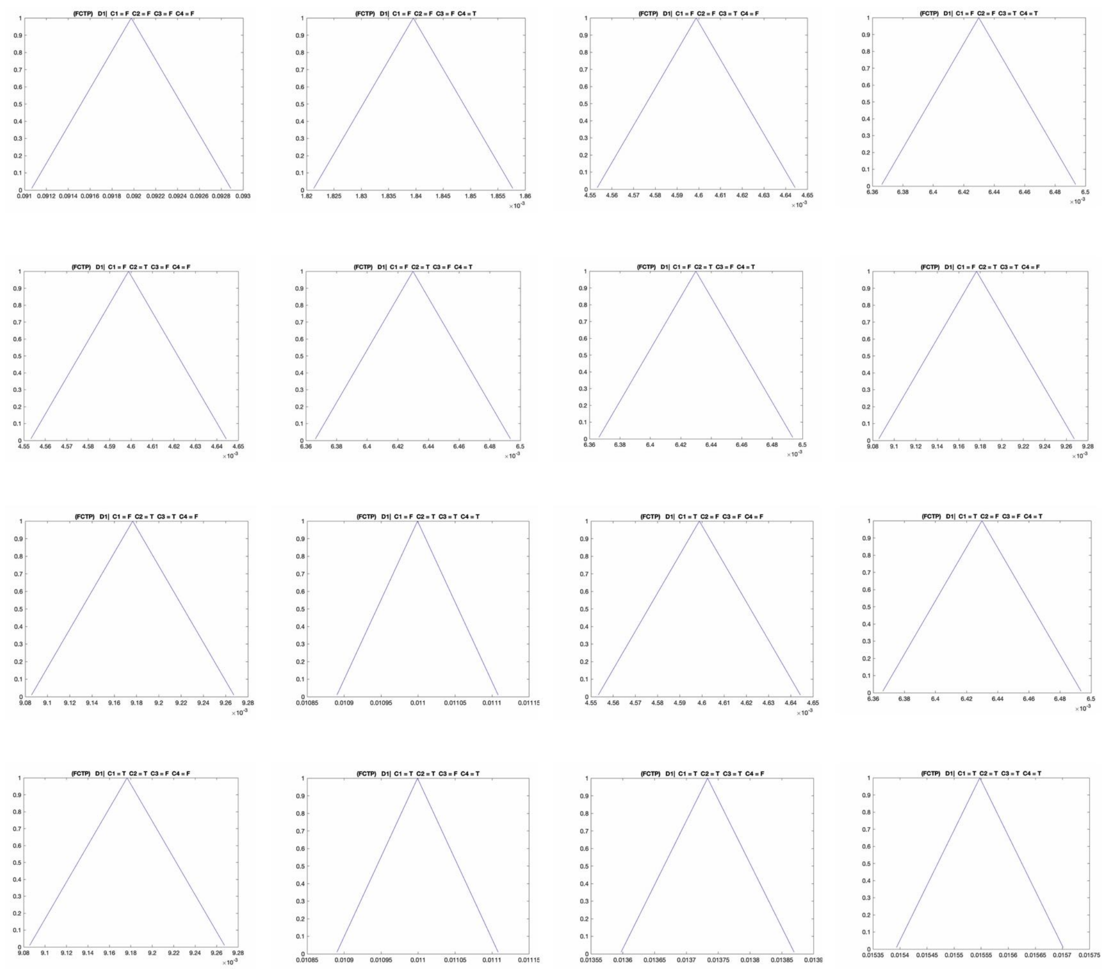


Figure 5.5: Fuzzy CPDs of D1

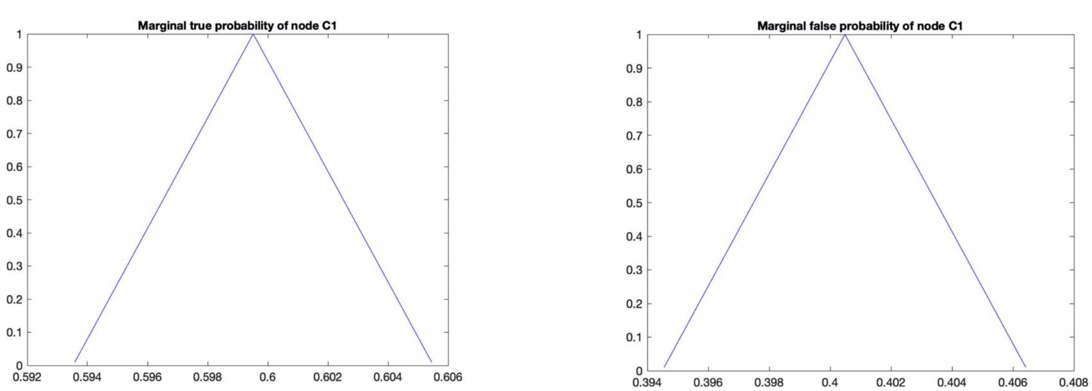


Figure 5.6: Fuzzy MPD of C1

other combinations. Therefore, reviewers consider the occurrence of any human associated failure of control systems (Dl) is highly unlikely to be by any employee physical condition (C1).

Aside from conditional probability, marginal probabilities are found out using equations in section 5.2.3. Figure 5.6 illustrates fuzzy calculations of both occurrence and non-occurrence of a marginal node 'D1'. The ranges of $\mu_{D1T}(x)$ and $\mu_{C1_F}(x)$ are different from each other as the probabilities are composed of one percent.

5.3.2 Prior and posterior calculations

Having obtained Marginal and Conditional Probability Distributions of all nodes in the HEDC, the unique proposed BN is set to perform an analytic understanding of human-error risks. In order to this, joint probabilities of all conditions have been revealed, which has enabled prior probabilities of the nodes in the proposed Bayesian network to be conducted. A prior probability of a specific human error in the HEDC might be expressed to deliver definite information about how it is evaluated and prioritised.

On the other hand, the significant feature of a BN is in reversing probabilities of events on account of observations of others. As a result, not only can the posterior probabilities of any human errors be determined, but also the probabilities in the network are able to be updated. The inference of posterior probability calculation has begun with the assignment of the node 'Y', which is leaf node; that is, derailment. The node has been calculated assuming that the observation takes place.

Table 5.15 illustrates the mathematical expression of priori ($\mu_i(x)_{\text{Prior}}$) and posteriori ($\mu_i(x)_{\text{Posterior}}$) occurrence of many significant nodes. The impact of choosing lower and higher bound of fuzzy membership function is clearly seen as a_{prior} and c_{prior} as well as $a_{posterior}$ and $c_{posterior}$ are found out to not be diverted considerably from b_{prior} and $b_{posterior}$, respectively. This means that the proposed unique methodology gives rise to much precise results compared to previous studies at its kind. As the proposed Bayesian network has 59 nodes, majority of which possess conditional dependencies to one (or more) other node(s), posterior probabilities seem to not be diverted from prior posterior. Another reason for this desired behaviour is of the sample of a large number of railway employees, which enables the study to have solid comprehensive data.

Whether $\mu_i(x)_{\text{ Prior}}$ or $\mu_i(x)_{\text{ Posterior}}$ is considered, human errors associated with train handling (B) and control systems (D) are found out to influence derailments at an ignorable level. Brake of use (A), speed (E), flagging, fixed, hand and radio signals (F) along with use of switches (G) are ascertained to be the primary reasons for human error-related derailments at turnouts. Moreover, employee physical condition (C) is identified to be the most derailment-driving cause in the HEDC.

5.3.3 Sensitivity analysis

The proposed Bayesian network might be identified to be exposed by the changes in marginal probabilities of employee physical conditions (C1, C2, C3, C4), as the majority of nodes are in relation to them, and thereby the output of the network (Y) is affected by these dependent nodes as well as the marginals. Therefore, a study of how the uncertainty in the output of this Bayesian-based mathematical model could be apportioned is necessary to be examined under different inputs of employee physical conditions.

Figure 5.7, obtained throughout AgenaRisk, illustrates the posterior proba-

Table 5.15: Lowest, middle and highest values of fuzzy prior and posterior distributions

			$\mu_i(x)$ Prior			$\mu_i(x)$ Prior		
Node Names (i)	Marginal Probability	$x = x_1$	$x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
A1	No	True	0.599	0.594	0.587	0.607	0.613	0.617
A2	No	True	0.464	0.459	0.455	0.468	0.472	0.476
A3	No	True	0.321	0.318	0.315	0.322	0.325	0.328
A4	No	True	0.006	0.006	0.006	0.006	0.006	0.006
A5	No	True	0.039	0.039	0.038	0.038	0.039	0.039
A6	No	True	0.007	0.007	0.007	0.007	0.007	0.007
A7	No	True	0.002	0.002	0.002	0.002	0.002	0.002
C1	Yes	True	0.606	0.600	0.594	0.596	0.602	0.608
C2	Yes	True	0.661	0.654	0.647	0.649	0.656	0.663
C3	Yes	True	0.158	0.156	0.155	0.156	0.157	0.159
C4	Yes	True	0.179	0.177	0.175	0.175	0.177	0.179
E1	No	True	0.744	0.737	0.730	0.750	0.756	0.763
E2	No	True	0.522	0.517	0.512	0.530	0.534	0.538
F1	No	True	0.082	0.081	0.079	0.080	0.081	0.082
F2	No	True	0.081	0.080	0.079	0.080	0.081	0.082

Table 5.15 *(Continued)*.

Node Names (i)	Marginal Probability	$x = x_1$	$\mu_i(x)$ Prior			$\mu_i(x)$ Prior		
			$x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
F3	No	True	0.234	0.231	0.229	0.234	0.235	0.238
F4	No	True	0.122	0.121	0.120	0.121	0.122	0.123
F5	No	True	0.246	0.242	0.239	0.245	0.247	0.251
F6	No	True	0.040	0.040	0.040	0.040	0.040	0.040
F7	No	True	0.281	0.278	0.276	0.283	0.285	0.287
F8	No	True	0.171	0.169	0.168	0.171	0.172	0.174
F9	No	True	0.043	0.042	0.042	0.042	0.042	0.043
F10	No	True	0.029	0.029	0.029	0.029	0.029	0.029
F11	No	True	0.033	0.032	0.031	0.031	0.032	0.033
F12	No	True	0.327	0.323	0.320	0.329	0.332	0.336
F13	No	True	0.188	0.186	0.185	0.188	0.189	0.191
F14	No	True	0.100	0.099	0.098	0.099	0.100	0.101
D1	No	True	0.100	0.099	0.098	0.099	0.100	0.101
D2	No	True	0.075	0.073	0.072	0.073	0.074	0.075
B1	No	True	0.027	0.027	0.026	0.026	0.027	0.027

Table 5.15 *(Continued)*.

Node Names (i)	Marginal Probability	$x = x_1$	$\mu_i(x)$ Prior $x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$\mu_i(x)$ Prior $x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
B2	No	True	0.023	0.022	0.022	0.022	0.022	0.023
B3	No	True	0.018	0.018	0.018	0.018	0.018	0.018
B4	No	True	0.007	0.007	0.007	0.007	0.007	0.007
B5	No	True	0.008	0.008	0.008	0.008	0.008	0.008
B6	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B7	No	True	0.008	0.008	0.008	0.008	0.008	0.008
B8	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B9	No	True	0.015	0.015	0.015	0.015	0.015	0.015
B10	No	True	0.005	0.005	0.005	0.005	0.005	0.005
B11	No	True	0.006	0.006	0.006	0.006	0.006	0.006
B12	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B13	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B14	No	True	0.001	0.001	0.001	0.001	0.001	0.001
B15	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B16	No	True	0.002	0.002	0.002	0.002	0.002	0.002

Table 5.15 *(Continued)*.

Node Names (i)	Marginal Probability	$x = x_1$	$\mu_i(x)$ Prior			$\mu_i(x)$ Prior		
			$x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
G1	Yes	True	0.712	0.705	0.698	0.744	0.749	0.755
G2	Yes	True	0.265	0.262	0.259	0.268	0.270	0.273
G3	Yes	True	0.209	0.207	0.204	0.210	0.212	0.214
G4	Yes	True	0.199	0.197	0.195	0.200	0.202	0.204
G5	Yes	True	0.138	0.137	0.135	0.138	0.139	0.140
G6	Yes	True	0.242	0.239	0.237	0.244	0.246	0.249
A	No	True	0.537	0.529	0.521	0.572	0.577	0.583
B	No	True	0.012	0.012	0.012	0.012	0.012	0.012
C	No	True	0.659	0.649	0.639	0.643	0.653	0.662
D	No	True	0.024	0.024	0.024	0.027	0.027	0.027
E	No	True	0.568	0.558	0.549	0.611	0.617	0.624
F	No	True	0.337	0.331	0.326	0.365	0.368	0.374
G	No	True	0.615	0.609	0.595	0.691	0.701	0.704
Y	No	True	0.781	0.771	0.758	1.000	1.000	1.000

bilities of intermediate nodes A, B, D, E, F and G in response to changes in the inputs of C1, C2, C3 and C4. The bar lengths of tornado diagrams represent the extent to which the probability of the intermediate nodes varies. As seen on tornado diagrams, the probability of intermediate nodes is found out to be most influenced or sensitive to C1. The bars of C1 point out the range of changes in various target states for intermediate nodes. Around 1.5% of their current posterior value down and up is identified. Therefore, it can be said that the network is not affected much by a given specific set of variables defined by numerous scenarios.

5.3.4 Scenario generation

In many cases, scenarios based on Bayesian networks are developed to analyse probable future events by considering the possibility of some events that will not likely be available. Developments in railway risk management, and more importantly adaptation of them progress at a slow pace. Thus, the strategy of possible scenario is taken on the suspicious nodes making them ineffective in probability chain of HEDC. As a result, the authors take an action of elimination of Human errors associated with employee physical condition (i.e. employee asleep due to overworking) in the network as all attendees, whatever the occupation is, could exaggerate the results to benefit from high expression of this, or transferring problems on this kind of errors.

To eliminate such concerns, a new Bayesian inference with Boolean variables are assigned the marginal nodes C1 to 4 (0) and the Leaf node Y (1).

Figure 5.8 shows the highest value (b) of membership functions ($\mu_{i_b}(x)$) of all nodes in the network. Due to the nature of the posterior, C1 to 4 is ineffective, and result in ample drop in the probabilities of various intermediate nodes such as A1, A2. Although C1 to 4 are inferred as false, it is seen that D has a posterior

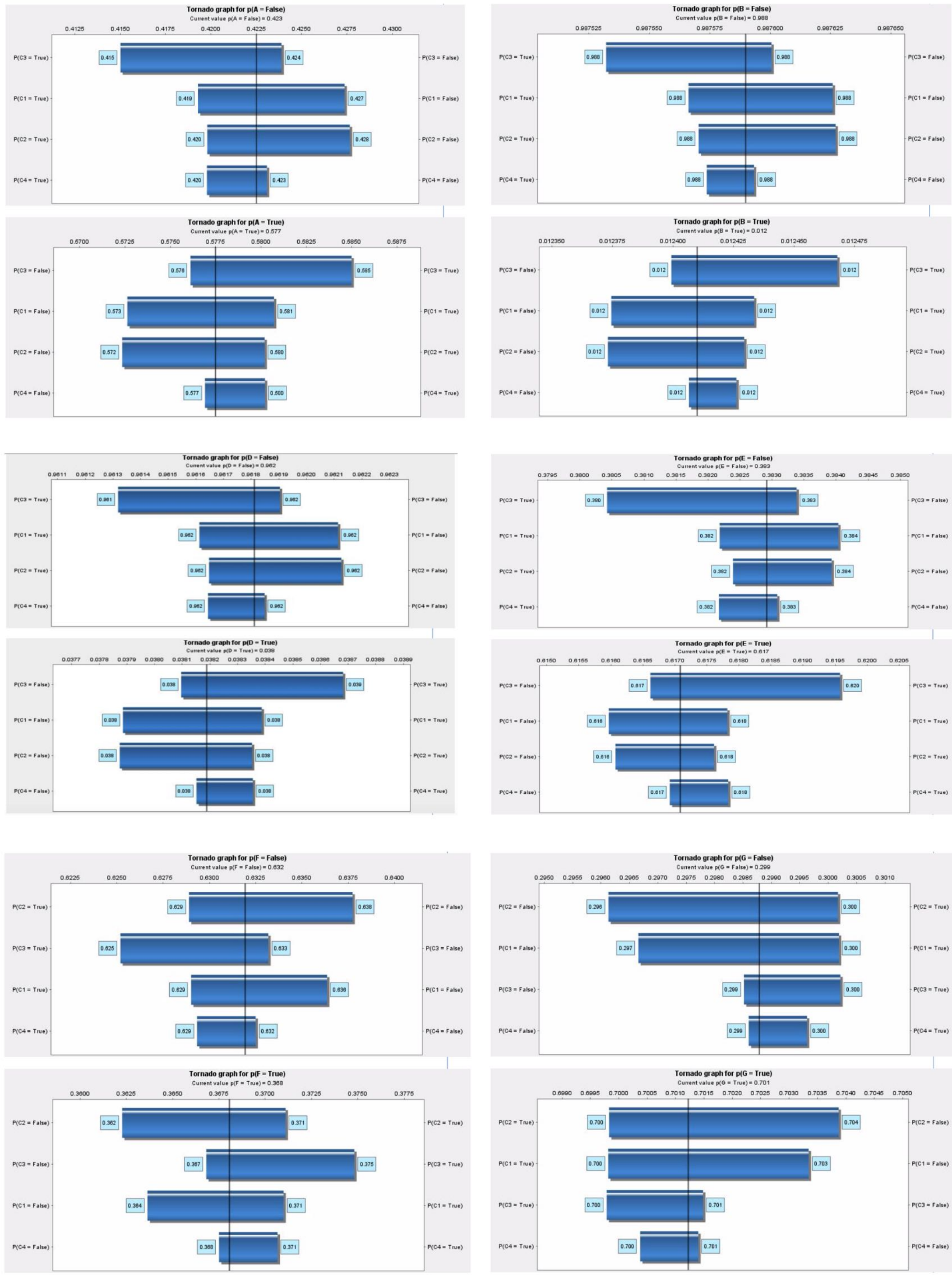


Figure 5.7: Sensitivity analysis of HEDC for the probability of all intermediate nodes being 'true' against probability changes of employee physical conditions.

probability of 2.64%. This is mainly from expert opinions on the probability that the observer having spotted any employee physical condition given that this observed condition is not impacted by C1 to 4. B, C and D are identified as negligible errors, whereas A, E, F and G are revealed to require an action to minimise the derailments that result from human errors.

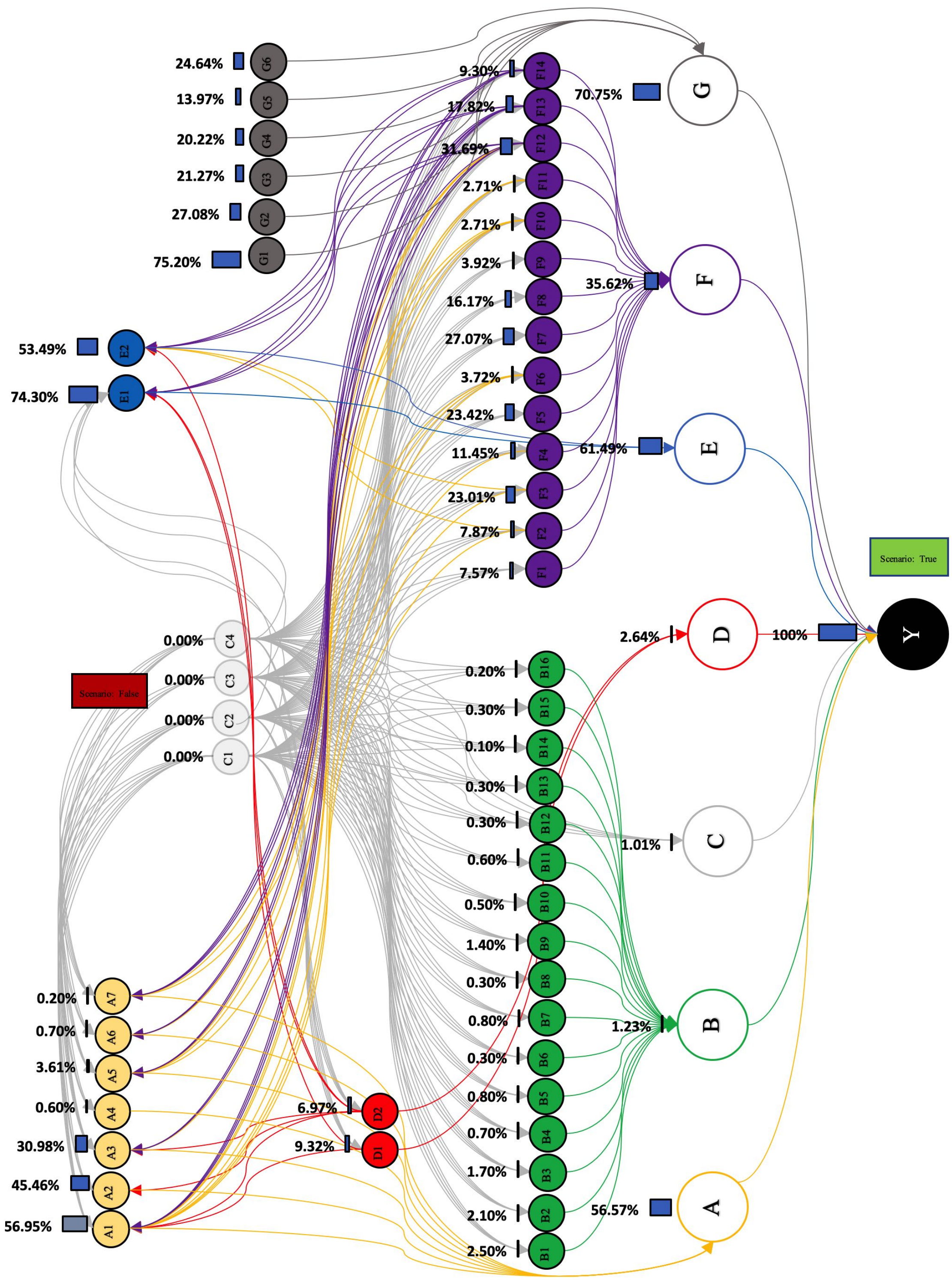


Figure 5.8: Results of the potential scenario for HEDC

5.4 Discussion

In this chapter, human error-based derailment (HEDC) causes at turnouts has been integrated into a Bayesian network (BN) in order to reveal and analyse the degree of contributing factors. The proposed novel methodology uses fuzzy membership functions to achieve a proper risk analysis and generate possible scenarios under uncertainty, so that the investigation of the system reliability and the identification of activities that could carry risk are performed. The discussion of the results is presented as follows:

From a perspective of posterior-based (P(Y) =1) risk analyse, it is identified, as seen in Table 5.16, that the use of switches is the most violated type of human error group. Although the hand operation of switches is not common practice on urban railway network, they are occasionally still in operation at sidings on interprovincial main tracks in Turkey. It is also determined that failures at facing or trailing are expressed as a fundamental contribution to derailment at turnouts. The term refers to converging (trailing) and diverging (facing) in the direction of rail travel. Where interlockings and signalling are absent on Turkish rural areas, particularly facing turnouts is expressed to be remarkably hazardous, even though the Turkish code of practice follows FRA rules. This is fundamentally because the Turkish railway network is operated on single lines, which leads to the necessity of using a tremendous amount of sidings. Considering a high volume of railway traffic that the Turkish railway network has, and exhausted train drivers from overwork, the high-risk proportion of errors at using switches is seen to be rational.

On the other hand, brake of use (A), employee physical conditions (C) and

[7] This is air brakes (only in use when the brake pipe air pressure is reduced) that machinists can apply on the locos only.

Table 5.16: Distribution of risk proportions through the major nodes

		Brake of Use	Train Handling	Employee Physical Conditions	Control Systems	Speed	Flagging, Fixed, Hand and Radio Signals	Use of Switches
$P(Y) = 1$	$\mu_i(x)_{\text{Posterior}}$	0.577	0.012	0.653	0.027	0.617	0.356	0.701
	Risk proportion	0.220	0.010	0.210	0.010	0.210	0.120	0.240
P(Y) = 1 P(Cl to 4) = 0	$\mu_i(x)_{\text{Posterior}}$	0.566	0.012	0.010	0.026	0.615	0.331	0.707
	Risk proportion	0.250	0.010	0.000	0.010	0.270	0.150	0.310

speed (E) are identified to be other significant derailment drivers at turnouts. In Turkish railway operation, three types of brakes are used, namely: (aside from emergency brake that all rolling stock have) independent brakes [7], automatic brakes[8] and dynamic brakes[9]. These brakes can be controlled by machinists, and are seldom used as automatic train protection[10] (ATP) have been applied to a great deal of rolling stock in Turkey. It is identified that the remaining trains, albeit limited in number, are seen to be a potential source of adverse effect on the derailments. Shutting down the ATP system (mostly by machinists) is also identified to seldom take place in Turkish railway operations, which leads to an outrageous risk of derailment at turnouts. In other respects, the majority of interviewees underlined that the heavy workload of railway employees presents due to two fundamental reasons: 1) limited number of the employees against increasing over time; 2) increased demand for railway transportation. This drives stress and job dissatisfaction, both of which are likely to result in human errors in a direct or indirect way. As a direct way, employee physical conditions are determined to be one of the major risk groups with a proportion of 21%. Where ATP or signal do not exist, the critical speed range that is identified for particular railway turnouts might be exceeded, which has often been stressed as the most costly type of human error, due to the high amounts of damage not only to the switch, but also, depending on the point of derailment, wagons and locomotives.

From the perspective of scenario-based (P(Y) = 1 & P(Cl to 4) = 0) risk

[8] The brake system takes action automatically applying not only a loco but the rest of the train as well. The amount of braking by this system is dependent on the amount that the system is charged.

[9] The traction motors of a rolling stock are turned to electric generators which produce current either dissipated as heat by the braking grid or fed back into the power supply system. This system allows only to decrease the speed.

[10] The speed of the train is continuously monitored, and the driver with speed limit information on particular tracks is provided to machinists, and ATP indicates a warning if any failure at decreasing the speed takes place. Moreover, if ignored the brakes are automatically applied to stop safely the train.

analyse, an indirect way of risk analyse, an indirect way of employee physical conditions is pinpointed by means of fluctuation in proportional changes of results between $P(Y) = 1$ and $P(Y) = 1$ & $P(C1 \text{ to } 4) = 0$. The impact of Employee physical conditions on derailments plunged to almost 0% due to the nature of a Bayesian network. It can be highlighted that brake of use is affected more than the others by employee physical condition since risk proportion increases relatively less. In contrast to risk proportion of brake of use, that of speed and use of switch rise by 6% and 7%, respectively. The reason behind this pattern is that the probability of brake of use is also contributed by employee physical conditions, whereas speed is partly affected (due to E1, see Figure 5.4). Where the absence of the contribution in conditional probability calculation, as expected, the probability of brake of use becomes lower. However, as a posterior probability (P(Y) = 1) takes place, it has taken roughly the proportion of 3% from employee physical conditions.

5.5 Conclusion

Chapter 5 proposes a novel Bayesian-network based methodology to cope with human errors causing derailment at railway turnout. As underlined in Chapter 3, the infiuence of human errors on derailments is considerably high. Chapter 5 specified human errors into seven groups, namely use of brake, train handling, employee's physical condition, control systems, speed, signal problems and use of switch. The study provides concrete insight into the rail industry from the perspective of human error involving derailments at railway turnouts systems. The findings show that human error associated with employee physical condition is the most influential risk group to train derailments. This risk group is followed in order by human error associated with use of switch and speed. The most common type of human error related to employee physical condition is found to be 'employee restricted in work or motion'. 'Moveable point switch frog improperly lined, hand-operated' and 'switching movement, excessive speed' are identified to be the primary reasons under human error associated with use of switch and speed, respectively. It is said that the thesis, through this chapter, establishes a novel risk management framework related particularly to human errors and offer this framework as an applicable tool for the current demand of railway industry. Moreover, over 50 nodes, each of which is appointed to a specific error, are integrated into each other through the novel proposed methodology. The proposed unique network, which is a part of this novel methodology, has potential to be used in any accident-oriented artificial application in future railway application.

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CHAPTER 6

A BAYESIAN-BASED HIERARCHICAL MODEL FOR ANALYSIS OF CLIMATE ON HAZARDOUS TURNOUT COMPONENT FAILURES

6.1 Introduction

In the light of Chapter 4, it can be said that the most frequently encountered primary or influential factors related to derailments at railway turnouts is the failures of turnout constituents. There has been increased focus on the examination of these failures in the field of railway engineering in recent years due to high frequency of occurrence(Liu et al., 2012). An actual train flow model has been developed to reflect the susceptibilities of railway networks in the case of both individual and multiple constituent failures, apart from those related to turnouts (Ouyang et al., 2014).

Discussions have been made with respect to safety-oriented maintenance in order to optimally restore railway turnout systems (Ishak et al., 2016). It has been identified that there is a significant relationship between weather trends and the rate of turnout constituent failure, which subsequently cause derailments (Dindar et al., 2016). A Bayesian failure prediction based on networks, which does not generate any predictions of derailment, has been modelled to assess the impact of climatic conditions on the failure of railway turnout (RTs) constituents (Wang et al., 2017). However, this referred study cannot be applied to larger-scale analyses as weather trends frequently change. Furthermore, the methodology employed in Wang et al.'s study did not address the outcomes of such failures. The research provided recommendations to the sector and railway authorities with regard to how regional segmentation could be applied based on weather trends, while failures that cause derailments could be forecasted across the whole railway network over a specific time period. A discussion was presented in regard to the correspondence of the count data to different covariates y to different covariates $\mathrm{x} = [1; \mathrm{x}^1, \ldots, \mathrm{x}^\mathrm{p}]^\mathrm{T}$, while multilevel modelling with set variables and random coefficients was also included (Kreft and De Leeuw, 1998). The exchangeability of hyperparamaters on multi-level hierarchical Bayesian analysis was also presented and enhanced (Albert, 1987,?). Hauer investigated safety estimations on sections of road in relation to accidents by applying the Empirical Bayes technique and utilising Rukhin's approach (Hauer, 2001). Additionally, the Gibbs sampler, in combination with a Metropolis-Hastings (GSMH) algorithm, was developed (Robert and Casella, 2004). GSMH has frequently been employed to assess the reliability for the prediction of different types of engineering networks, For example, a Bayesian network that takes into account light signals, speed restrictions and different aspects of railway infrastructure was formulated in 2016 with an aim at determining the safety levels of moving railway vehicles on specific railway networks (Castillo et al., 2016).

In this thesis, distinctive levels of exposure collated during the GIS procedure (geographical information system) have been incorporated into a multi-level Bayesian model, and then each factor that has the potential to influence the frequency of derailment incidents in the individual regions has been levelled out through the application of the exchangeability model. The distinctions between the present study and those conducted previously are that firstly, the scope of the investigation is significantly wider as it includes the whole railway network within the United States. Secondly, it considers the failure of railway constituents that ultimately cause derailments associated with turnout infrastructure. Thirdly, one of the unique aspects of the study is that a hypothesis is established to emphasise that all types of safety-risk analysis focused on derailments resulting from constituent defects on a broader scale could be acceptable on the condition that different regions are segmented based on weather trends.

6.2 Methods

As discussed in Chapter 2, it is necessary to conduct an analysis on failure rates and severity to reveal the risk of derailment at RTs. Therefore, a structure, capable of estimating the rates of the derailment accidents within the zones of a particular climate region, is modelled especially for the derailment cases. Estimates for the probability of derailments within each zone need to be dealt with separately through the same approaches embedded in mathematical formulae, albeit different statistical inputs since the varied statistical realisation of the same sample space is constructed and many different independent random outcomes present. Therefore, a novel mathematical modelling consists of precipitation and temperature elements ,each of which handles its unique count data (y_j).

6.2.1 Data exploration

6.2.1.1 Data reliability and use

The Federal Railway Administration (FRA) is an official railway authority under the US Department of Transportation that was originally established to implement railway assistance schemes, amalgamate governmental reinforcement of railway transportation projects, perform research and development to enhance the overall safety of railway networks as well as railway transportation policies in the United States, to facilitate the rejuvenation of the railway passenger services provided in the Northeast Corridor, and to enforce railway safety rules for railway companies and associated bodies. To successfully meet these requirements, the FRA gathers and examines information from both railway companies as well as different railway maintenance providers and then publishes the findings on a monthly and yearly basis.

According to the Federal Railroad Administration (FRA) regulations, Title 49, Part 225 of the Code of Federal Regulations, all railway operators in the US are mandated to utilise the most recent FRA Guide for Preparing Accident Incident Reports (”Guide” or ”reporting guide”) in the preparation of its relevant monthly publications(FRA, 2003). These publications reporting on recent accidents are designed to disclose the reasons, characteristics and particular scenarios in relation to such incidents.

This study only employs reports released by the FRA covering accidents that surpassed either a certain financial threshold or human losses including passengers and railway employees, or both. Damages deemed worthy of reporting include labour costs as well as additional financial expenses incurred in relation to the replacement or restoration of impaired track, track infrastructure, on-track appliances, track bed or signalling equipment. The FRA accident reports do not include expenses associated with removing train wreckage, cleaning environmental impacts or damage to lading when calculating the overall damages. Further to reportable damages, all victims of such incidents are officially noted to record the extent and types of injuries and fatalities throughout the United States. These reports additionally include specific details on the accident location as well as the environmental conditions at the time of the derailment.

It has been demonstrated that both precipitation and temperature are significantly influential factors during incidents of railway turnouts constituent failure (Dindar and Kaewunruen, 2017, Wang et al., 2017). To facilitate the process of collating data related to both aspects, accident locations are utilised. NORA, the official body responsible for climate within the US, publishes precipitation and temperature data based on a summary of daily observations. NOVA’s collated information has been verified via the suggested map (Figure 6.1). As it can be observed that both sets of values are compatible, the decision has been made to utilise the map as a representation of climate zones. The regions are numbered from 1 through to 7, denoting the hottest to coldest regions on the basis of temperature, whereas the levels of humidity are labelled as A, B and C.

6.2.1.2 Data selection

There is a total of 50 states within the US, and the FRA gathers information on derailments from a variety of different regional railway companies who offer services within each of these states. Every state is affected by distinct variables such as temperature, precipitation and the density of traffic, in addition to a track class, which is considered an intersectional variable. The present study does not consider the states Alaska and Hawaii as there is no railway network in Hawaii, while the prevalence of severe cold weather conditions in Alaska could lead to abnormal results diverging from the anticipated estimates, even though the traffic density is relatively low.

As part of the FRA's authority, it has designated six categories of railway track, which are the indications of the track quality, and each is assigned specific maximum speed constraints.The present study will specifically focus on derailment estimations on whole networks on an individual state basis. The assumption is made in a way that the state of turnouts in addition to their maintenance condition is similar across all states.

Conversely, both the size of the railway network and traffic density have relevance for the potential to experience derailment within the states (rail ton-miles per track mile per year[1]). Hence, the chosen data can be verified to provide

[1]The product of yearly overall weight (inclusive of both the loco and full/empty wagon weight) and the total distance travelled by a train vehicle.

Table 6.1: Reported failures of crossing noses, switches and track appliances at RTs.

n	*FRA Code*	*Description of failures*
1	T301	Derail, defective
2	T302	Expansion joint failed or malfunctioned
3	T303	Guard rail loose/broken or dislocated
4	T304	Railroad crossing nose, worn or broken
5	T307	Spring/power switch mechanism malfunction
6	T308	Stock rail worn, broken or disconnected
7	T309	Switch (hand operated) stand mechanism broken, loose, or worn
8	T310	Switch connecting or operating rod is broken or defective
9	T311	Switch damaged or out of adjustment
10	T312	Switch lug./crank broken
11	T313	Switch out of adjustment because of insufficient rail anchoring
12	T314	Switch point worn or broken
13	T315	Switch rod worn, bent, broken, or disconnected
14	T316	Turnout crossing nose (rigid) worn, or broken
15	T317	Turnout crossing nose (self-guarded), worn or broken
16	T318	Turnout crossing nose (spring) worn or broken
17	T319	Switch point gapped (between switch point and stock rail)
18	T399	Other crossing nose, switch and track appliance defect

information on the extent to which turnouts throughout the whole network are vulnerable.

The occurrence of derailment at RTs might lead to one of, or a combination of the following consequences: financial loss, loss of time, damage to functioning railway components, personal injury and even loss of life. This study is limited to the probability (P) of the hazard, as derailments associated with component failures in railway turnouts have similar consequences, namely casualty and financial, and the main focus of the research reveals an exact relationship between derailments and climate. The database of the research utilised from the FRA[2] -accident reports is shortened through the following official accident codes, shown in Table 6.1. The FRA codes are selected considering as to whether to associate with

[2]The Federal Railroad Administration, which is a US official railway agency.

railway turnouts.That is, the description of failure in this study is only related to various component failures of railway turnout. The FRA discretises RT-related component failures in 18 types of accident, each of which responds to different failures at RTs, as seen in Table 6.1.

6.2.1.3 Region selection

As previously mentioned in both Section 1 and Chapter 5, it is widely acknowledged that climatic trends have significant effects on the likelihood of train derailments at RTs. Accordingly, different climate areas consisting of either partial or full coverage of the states are chosen based on the yearly volume of precipitation and the yearly temperature average.

Due to the fact that climate can be affected by various different factors, such as closeness to large expanses of water, altitude, attitude, latitude and land features, the weather trends within the United States exhibit considerable variance. Thus, it is possible to conduct a climate classification to facilitate the understanding of the possible susceptibility of RT constituents to different weather conditions in the analyses. The US is regionalised by applying hierarchical cluster analysis on temperature and precipitation statistics, which seems to produce a group of potential clustering levels (Fovell and Fovell, 1993).

However, recently conducted research has enabled the determination of suitable climate specification for US counties, delineating the climate zone designations utilised by the US Department of Energy Building America Program (Baechler et al., 2013).

Figure 6.1 depicts the regional classification on the basis of average temperatures (TBCZs)[3] and precipitation (PBCZs)[4]. The map is divided from left to

[3]Temperature based climate zones
[4]Precipitation based climate zones

right to emphasise the precipitation level (A to C), and climate regions (1 to 7) are allocated to demonstrate the monthly average temperature degree for each zone. More precisely, climate region 4, which is highlighted with a yellow colour on the map, could be applicable for regions characterised by medium temperatures in addition to a marine, dry, or moisture regime.

As an illustration of the variety of weather trends within the US, the study will focus on seven specific states, which are shown in Table 6.2 along with their different weather-related trends. In combination, it is assumed that the states represent the average regime of the overall US climate, taking into the account the magnitude of the seven weather regions as well as the three moisture regimes within the US. However, Zone 1 is not incorporated into the coverage as its small size renders it irrelevant.

Hence, it can be clearly observed that it is important to focus on the analysis of derailment on the basis of the individual zones rather than states, as each state may consist of various climate regions.

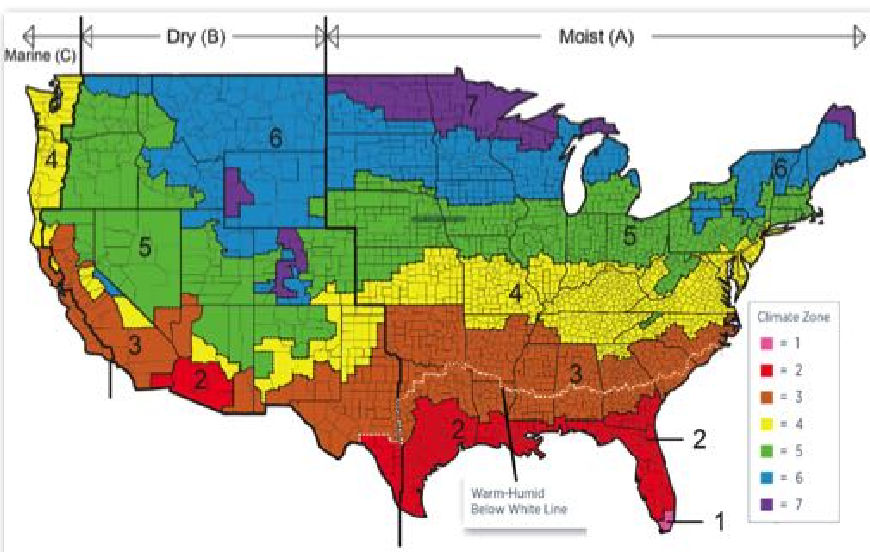


Figure 6.1: Seven US climate regions.

Table 6.2: States and their climate chracteristics

The Name of State	Climate Zones	Moisture Regime	Average Annual Temperature (°C)	Average Annual Precipitation (mm)
Illinois (IL)	5 & 6	A	10.8 °C	991 mm
Kansas (KA)	4 & 5	A	13.0 °C	992 mm
Nebraska (NE)	5	A	10.4 °C	768 mm
North Dakota (ND)	6&7	A	6.0 °C	453 mm
Oregon (OR)	4 & 5	B & C	11.7 °C	1006 mm
Texas (TX)	2, 3 & 4	A & B	17.7 °C	623 mm
Utah (UT)	5 & 6	B	12.7 °C	472 mm

6.2.2 Anatomy of turnout use in the US railway network

Although existing research examining railway turnouts in order to facilitate smooth railway functionality has been relatively thorough, there are still deficiencies in comparison to different kinds of research in the field of railway transportation. The underlying reasons for this could be the absence of prior research and exhaustive data collection. In this section, this thesis also intends to provide various amounts of data that will be beneficial for future studies.

6.2.2.1 Analytics

The volume of passengers and cargo users of railway services within the United States is not as large as one might assume given the magnitude of the climate zones. Hence, ArcGIS, which is an instrument founded on the geographic information system (GIS) designed to be used with layers providing a variety of geographic data, is employed. It could be stated that the layers are reliable as they represent a complete database covering the entirety of the country's railway networks and are given by formal bodies[5]. As a fundamental aspect of spatial analysis, GIS layers that include distinct types of information are utilised to de-

[5]https://www.arcgis.com/home/item.html?id=088a858aa479444fae9d3bade2d457e5.

termine the levels of exposure within the regions to derailed trains at RTs. The lower GIS layer shown in Figure 6.2 includes data in relation to every county inside the geographic coordinate systems of the selected states. The central layer (climate regions) indicate the regional boundaries of each weather trend, whereas the upper layer (the railway network within the United States) is utilised to ascertain both the traffic density and the amount of railway turnouts in terms of the location of each county on the map of the US. ArcGIS was only employed to calculate the volume of turnouts and derailment locations inside the regions. Initially, the turnout counts and volume of traffic for every turnout were determined (approximately 80,000). Subsequently, the analysis began the process of identifying every turnout in the divided region in order to facilitate the extraction of suitable data.

It appears that the derailment frequency is governed by a certain railway traffic measurement, like car-miles, train-miles of million gross tons (MGT) (Anderson and Barkan, 2004, Barkan et al., 2003, Treichel and Barkan, 1993). Hence, for the purposes of this thesis, traffic density will be defined in terms of MGT.

6.2.2.2 Identification of rail-Turnout characteristics by the states and the climate Regions

For the purposes of establishing mathematical reasoning in regard to whether climate patterns can influence the failure of turnout constituents leading to derailed trains, selected regions and exposures[6], are demonstrated in this part. Section 6.2 shows how exposure is calculated on the basis of the aforementioned numerical values.

It has been emphasised that the current research is not conducted on the basis

[6]Being in a scenario that has a certain contributory risk of involvement in train derailments associated with turnouts. Exposure consists of turnout counts (ρ) and railway trafic (φ).

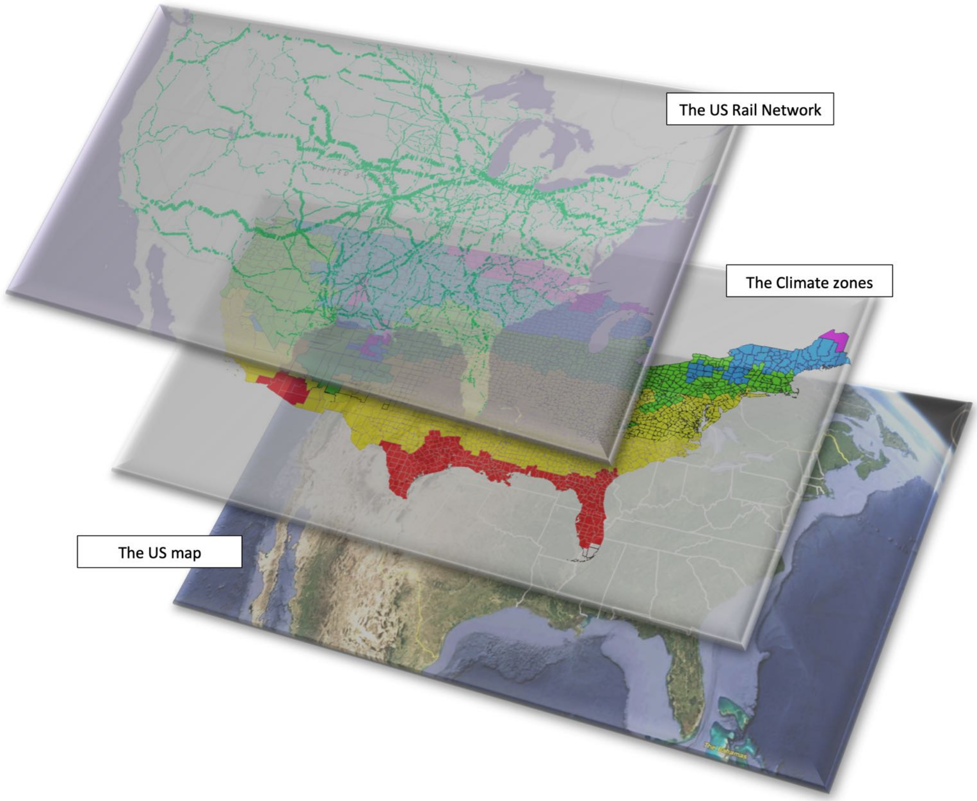


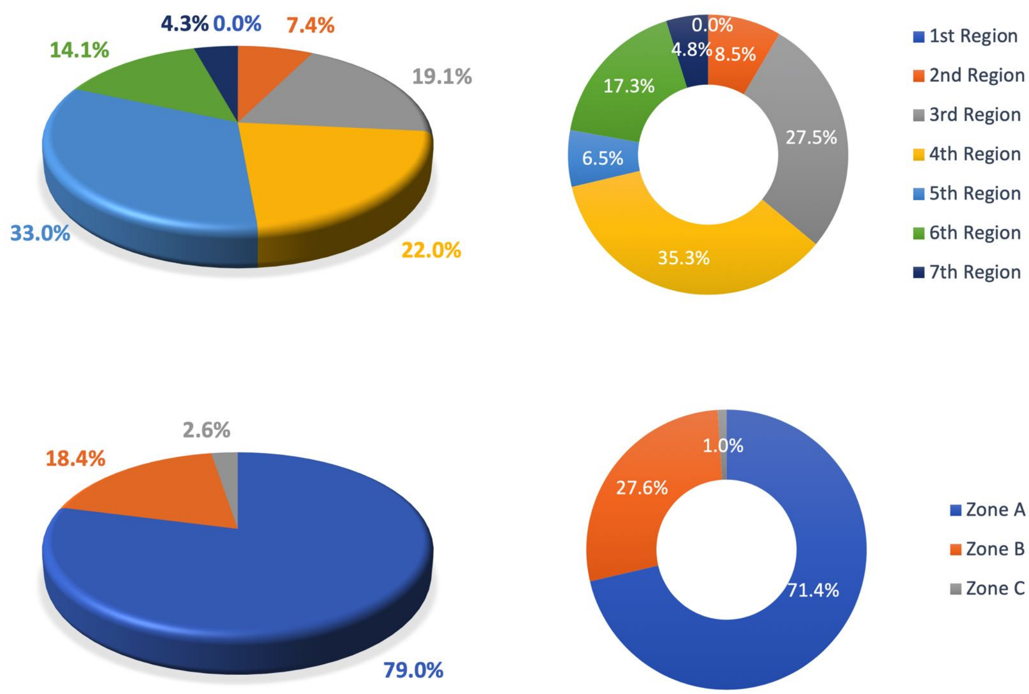
Figure 6.2: Stacked layers for spatial analysis on ArcGIS.

of exposure by individual state, but on exposure in terms of climate zone in order to firstly determine the effects of weather on derailments[7] followed by verifiable derailment estimates taking these effects into account. Therefore, the distribution of the indicators by climate zones and regions, see 3.3, is shown in Figure 6.3.

It is observed that there are almost 80,000 turnouts in operation across the railway network in the United States. Furthermore, the overall yearly amount of trail traffic crossing these turnouts is approximately 700,000 MGT. Hence, the distributions identified for the seven regions and three zones conform with and mirror actual recorded counts and values, as demonstrated in Figure 6.3.

Moreover, Figure 6.4 depicts the first attempt in the open literature to investigate turnout counts and overall density of traffic across turnouts. Hence, the

[7] The scope of the research is constrained to turnout constituent defects that cause derailments.



(a) Turnout counts (ρ) **(b)** Traffic (φ)

Figure 6.3: Proportions of turnout counts (ρ) and proportions of railway traffic (φ) across the 7 regions and 3 zones

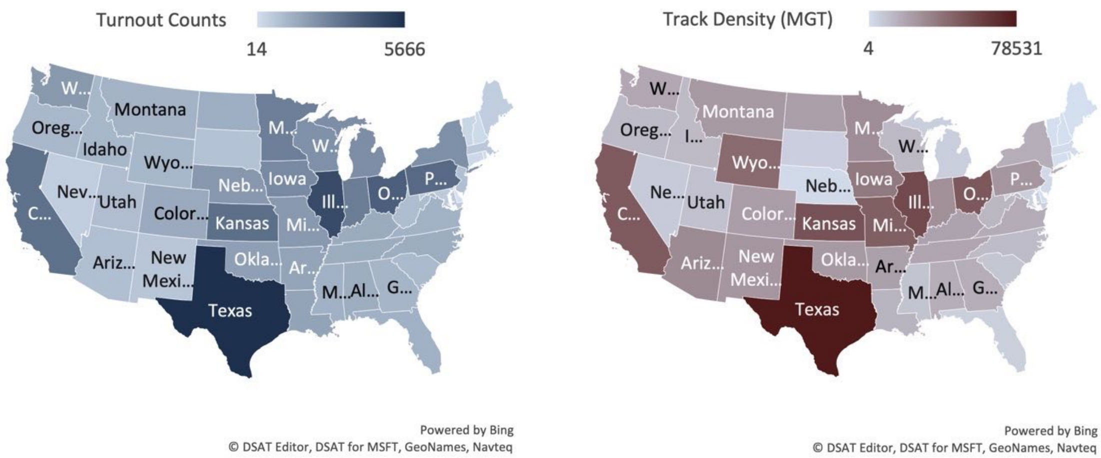


Figure 6.4: The number of usable turnouts and the volume of traffic over them across US railway network.

manner in which these two exposure indicators are distributed across different states within the United States is shown. Based on the available data, it might be assumed that Texas experiences the largest volume of derailments as the indicators for both turnout and traffic density are the highest for this state. Texas is then followed by Illinois, California, Ohio and Kansas, respectively.

6.2.3 Hierarchical modelling through unique exposure levels

This study is established on a novel Bayesian-hierarchical model to identify environmental factors on derailment cases, particularly at RTs. The model gives the simultaneous mathematical estimation of the true failure rates from each climate region and each US state. As all regions often comprise of different states, causing unique volumes of railway traffic, a two-stage Bayesian-hierarchical model[8], a mixture of gamma distributions with different hyper-parameters and parame-

[8] It is calculated through the LearnBayes Pack in Software R.

ters, is used to obtain more accurate estimates and illustrate exchangeability of prior knowledge by which the true component failure rates of RTs are assigned on a multi-layer Bayesian structure. The posterior distribution of the hyper-parameters, along with the Metropolis-Hasting technique is presented to perform a simulation from nine unique gamma distributions corresponding to the regions.

The study relies on derailment counts over a specific period of time. Thus, data distribution, which is statistically a function illustrating all the possible values of such given derailment data, can be obtained as follows:

$$y \sim f(y \mid \theta) \tag{6.1}$$

where y denotes derailment counts. The observations of derailment cases across the US are given distributions conditional on a parameter, which is θ in Eq. 6.1. On the other hand, the parameter is, in turn, assumed to be of distributions conditional on other parameters, called hyperparameters, as shown in the following Eq. 6.2:

$$\theta \sim g_1(\theta \mid \lambda) \tag{6.2}$$

where λ denotes generic hypermeters. On the other hand, Eq. 6.2 could be pronounced, as the prior vector θ follows the dependent function g_1. Hierarchical establishment, therefore, could be conducted by virtue of the distribution of λ.

$$\lambda \sim g_2(\lambda) \tag{6.3}$$

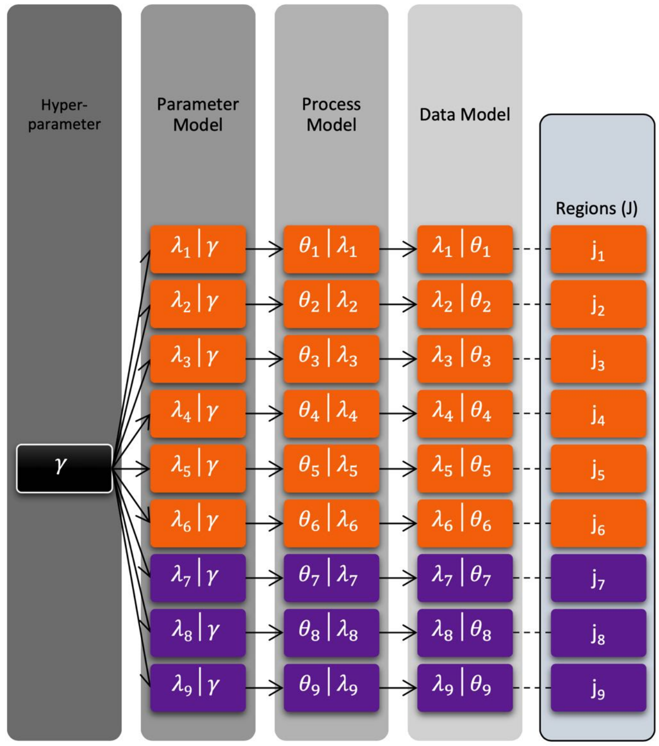


Figure 6.5: DAG of hierarchical modelling for temperature and precipitation-focused climate zones.

As indicated before, λ will be changed through nine regions.

6.2.4 Hierarchical prior choices

Even though six temperature and three precipitation-based climate zones (TBCZs & PBCZs) were pronounced for segmentation of climate characteristics prevailing in the US, the pink-coloured region, see Figures 6.1 and 6,2, will not be included due to several reasons underlined through Section 2. Therefore, it is considered that nine climate regions could give the response of the most reliable quantitative to the search objectives.

Let J be the generic symbol representing the chosen regions, and each J thus denotes a particular region. In order to show the hierarchical Bayesian model

[9] A graph that is directed and without cycles connecting the other edges.

of derailment-causing component failures for railway turnouts, a directed acyclic graph (DAG) [9] is illustrated in Figure 6.5. As seen, each climate region has unique random variable and derailment observations, and are symbolised as J1 to 6, which are represented in an orange colour and address differences in temperature, while the last three, coloured as purple in Figure 6.5, deal with precipitation across the US. Climate zones 2 to 7 in Figure 6.1 are named as 1 to 6 to ensure the elimination of ambiguity in the research.

All regions have been processed through three successive model layers. The data model, which is the first layer, presents a number of derailments within the climate regions. The process model corresponds to known parameters of the distribution, which is shown in Figure 6.3. The last model, the parameter model, regards a probabilistic distribution on hyperparameters of the known parameters.

6.2.5 Structural definition of the model

The identification of the impact of environmental factors, see Sec. 5.1.1, on derailment counts is one of the main concerns. Thus, the problem of learning about the rate of derailments is modelled region by region.

Let y_j refer to the number of derailment variables in future in one of the given nine regions 'j' and j= 1, . . . , J, J= 9. That is, the counts of events within a set unit of time are observed. In such situations, a probability model for the distribution of counts of derailments at RTs is considered to be a Poisson distribution [10] with mean π.

$$\pi_j = e_j.\lambda_j \tag{6.4}$$

[10] Poisson distributions are the discrete probability distributions of the number of events (e.g. derailment) occurring in a given time period (e.g. over the last five years), given the average number of times the event occurs over that time period.

where λ_j denotes the occurrence rate in one of the given nine regions and e_j is the exposure (per given period of time); see Section 2.2.2 for introductory information. The mathematical formula of the exposure is shown in Eq. 6.5.

$$e_j = \rho_j . \varphi_j \tag{6.5}$$

where ρ_j and φ_j donate the volume of railway traffic and the number of railway turnouts within the jth region of the assigned climates, respectively.

$$\mathrm{\lambda_j = \sum_{j=1}^{9} \sum_{s=1}^{s=48} y_{js}} \tag{6.6}$$

where $\mathrm{y_{js}}$ represents the number of derailment within the $j-th$ region of the assigned climate and the $s-th$ contiguous states with S= 1, . . . , s, s=48. Therefore, the distribution of possible unobserved derailments is conditional on the observed derailments and is given by

$$\mathrm{f\left(\tilde{y}_j|e_j, y\right) = \int f_P\left(y_j|\pi_j\right) g\left(\lambda_j|y\right) d\lambda} \tag{6.7}$$

where $\mathrm{g\left(\lambda_j|y\right)}$ and $\mathrm{f_P\left(y_j|\pi_j\right)}$ denote posterior density and Poisson sampling density, respectively. Eq. 6.7 is used to check if the consistency of the observed derailments within state ‘s‘ in one of the given climate regions ‘j‘, with s= 1, . . . , s, S=48, and j= 1, . . . , j, J=9 is present.

The target, therefore, is set to the estimate of the derailment rate at RTs per unit exposure (e). As expected, the total number of derailments throughout the regions is quite low. As a natural result, maximum likelihood estimate (MLE) cannot satisfy the estimate of $\tilde{\lambda}$ under any circumstances, as the denominator, $\mathrm{y_{j,s}}$, of MLE, $\tilde{\lambda}_{\mathrm{j,s}} = \mathrm{y_{j,s}/e}$, the equation will be pronounced with low discrete values, which gives rise to a poor estimate.

It, thus, is desired to benefit from Bayesian estimates having prior belief about the sizes of the derailment rates for the regions, which leads to opting for a gamma function with $(\mathrm{y_j}, \mathrm{e_j})$ density.

$$\mathrm{g}\left(\lambda|\mathrm{y_j}, \mathrm{e_j}\right) = \frac{1}{\mathrm{e_j^{\alpha}}\Gamma\left(\mathrm{y_j}\right)}\lambda^{\mathrm{y_j}-1}\exp\left(-\mathrm{e_j}\lambda\right) \tag{6.8}$$

On the other hand, Eq. 6.7 is also modelled through a non-informative Bayesian prior, which is $\mathrm{p}(\lambda) \propto \lambda^{-1}$ This is thought to give rise to a broadening discussion along with the intended model. The posterior density of λ might be obtained by [11].

$$\mathrm{g}\left(\lambda|\mathrm{y_j}, \mathrm{e_j}\right) \sim \sum_{\mathrm{j}=1}^{6}\left[\lambda^{\mathrm{y_j}-1}\exp\left(-\mathrm{e_j}\lambda\right)\right] \tag{6.9}$$

In order to make this discussion, Eq. 6.2 and Eq. 6.3 might be modelled through the following equation:

$$g_1\left(\lambda|\propto_1, \mu\right) = \frac{1}{\alpha_1\Gamma\left(\alpha_1\right)}\left(\frac{\alpha_1}{\mu}\right)^{\alpha_1}\exp\left(-\alpha_1\lambda/\mu\right), \lambda \in [0, +\infty) \tag{6.10}$$

[11] The equation 9 is designed for TBCZs as the index of the summation starts at 1 and goes to 6. The last value of the index is replaced with 3 for PBCZs. The same replacement is performed for Eq. 6.13 too.

where $g_1(\lambda|\propto_1, \mu)$ represents a gamma function used to generate samples of λ at the first level of the hierarchical structure. α and μ (parameters) are assumed to be a priori independent and follow inverse-gamma function (Albert, 1999, Gelman et al., 2006, Gustafson et al., 2006)

$$\begin{aligned} \propto_1 &\sim \mathcal{JG}\,(\alpha_2) \\ \mu &\sim \mathcal{IG}(\mathrm{a}, \mathrm{b}) \end{aligned} \tag{6.11}$$

As each region has unique posterior distribution considering independent values of π_j, the PDF is given by:

$$\pi_j \sim \mathcal{G}\,(y_j + \propto, e_i +^{\alpha} /\pi) \tag{6.12}$$

The marginal posterior density of the log hyper-parameters $(\log(\alpha), \log(\mu))$ is as the following equation:

$$\kappa \frac{\mathrm{z}}{\Gamma^6(\alpha)(\alpha+\mathrm{z})^2\mu} \sum_{j=1}^{6} \left[\frac{\alpha^{\alpha}\mu^{-\alpha}\Gamma\left(\alpha + \prod_{i=1}^{48} y_{ij}\right)}{(\propto /\mu + \pi_{\mathrm{j}})^{\left(\alpha + \prod_{\mathrm{i=1}}^{48} \mathrm{y_{ij}}\right)}} \right] \tag{6.13}$$

where is the constant of proportionality.

6.2.6 Metropolis-Hastings (H-M) algorithm

It is suggested that the posterior distribution function is sampled using the H-M algorithm (Hastings, 1970). This algorithm is expressed to bring out the Gibbs sampler, which is a Markov chain Monte Carlo (MCMC) algorithm, as a special case (Gelman et al., 2013).

The algorithm is used to approximate the output of Eq. 6.4 in Section 6.2.5, acquiring a sequence of random walk proposals from the Metropolis-Hastings algorithm itself.

The reason for the choice of Metropolis-Hastings for this study over Gibbs sampling is firstly that it is highly unlikely or practical to obtain the conditional distributions for each of the random variables in the suggested model, even within an environment with the full posterior joint density function (FPJDF) (Yildirim, 2012). Secondly, it is also unlikely that the posterior conditionals for each variable have a known form. As a result, samples from these conditionals cannot be drawn in an uncomplicated way (Lynch, 2007) .

6.3 Results

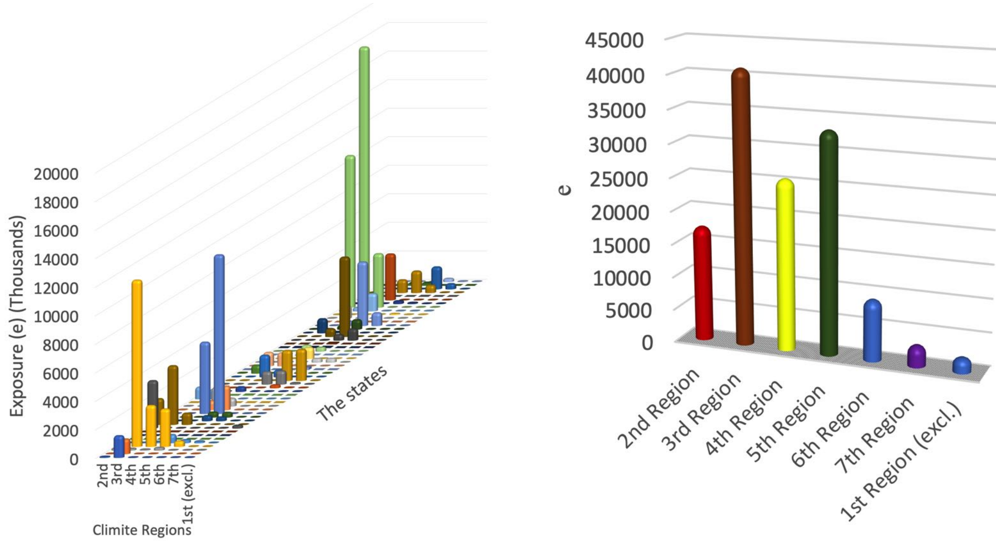
6.3.1 Fundamental findings of suggested data analysis

To deliver usable and useful information, a further aim is followed by this study, aside from estimating the significant characteristics of regional impacts on derailments, such as absolute numbers in various categories of the suggested framework. The distribution of categorised data and initial results of the suggested workflow are preferred to be firstly discussed. The fundamental statistical data obtained through the framework suggested in Figure 6.6 may, therefore, be presented.

Responses of the selected states to Eq. 6.5 are illustrated in Figure 6.6-a. Many states, such as Texas (green) and California (yellow), might be underlined to overpower the distribution of e total, whereas the others seem to be impacted by a low number of turnouts, a low number of railway traffic, or a combination of both, due to the mathematical nature of the Eq.5. It is worth noting that the 3D bar chart is not directly used to respond to the research question. Instead, region and state based exposures are illustrated. Figure 6.6-b illustrates the distribution of e through six regions from Region 2 (red) to Region 7 (purple), see Fig. 6.1 for a colour match.

It may be identified that derailments in Region 5 might be pronounced to be higher than the other five regions in a deterministic way. Additionally, Regions 3 and 4, which are coloured yellow and green respectively, can be asserted to yield more turnout-related derailments than Regions 6 and 2 together.

[12]To deliver the main point, and enhance visual quality, the Figure is plotted excluding a few states with extreme exposure, i.e. Texas, since they have relatively quite high values of y_j/π_j, which results in rounding up many values on a small area at a logarithmic scale.



(a) **(b)**

Figure 6.6: Exposure distribution by the states (a) and regions (b).

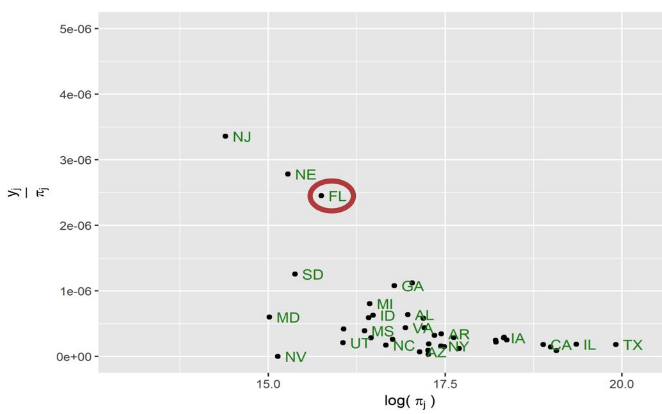


Figure 6.7: Derailment rates against log exposure for the majority of the states.

Nevertheless, Figure 6.7 [12] illustrates explicit inconsistency with this claim considering the derailment-based behaviour of states in Region 2. For instance, Florida, shown as FL in Figure 6.7, induces considerable unexpected risk (see Sec. 2) at turnout-related derailments, although Figure 6.6-b shows a quiet low rate exposure [13]. Therefore, this phenomenon might be elucidated to require a better mathematical algorithm, which includes a polled database not by states, but

[13] It is worth-noting that 1st region is almost composed of FL.

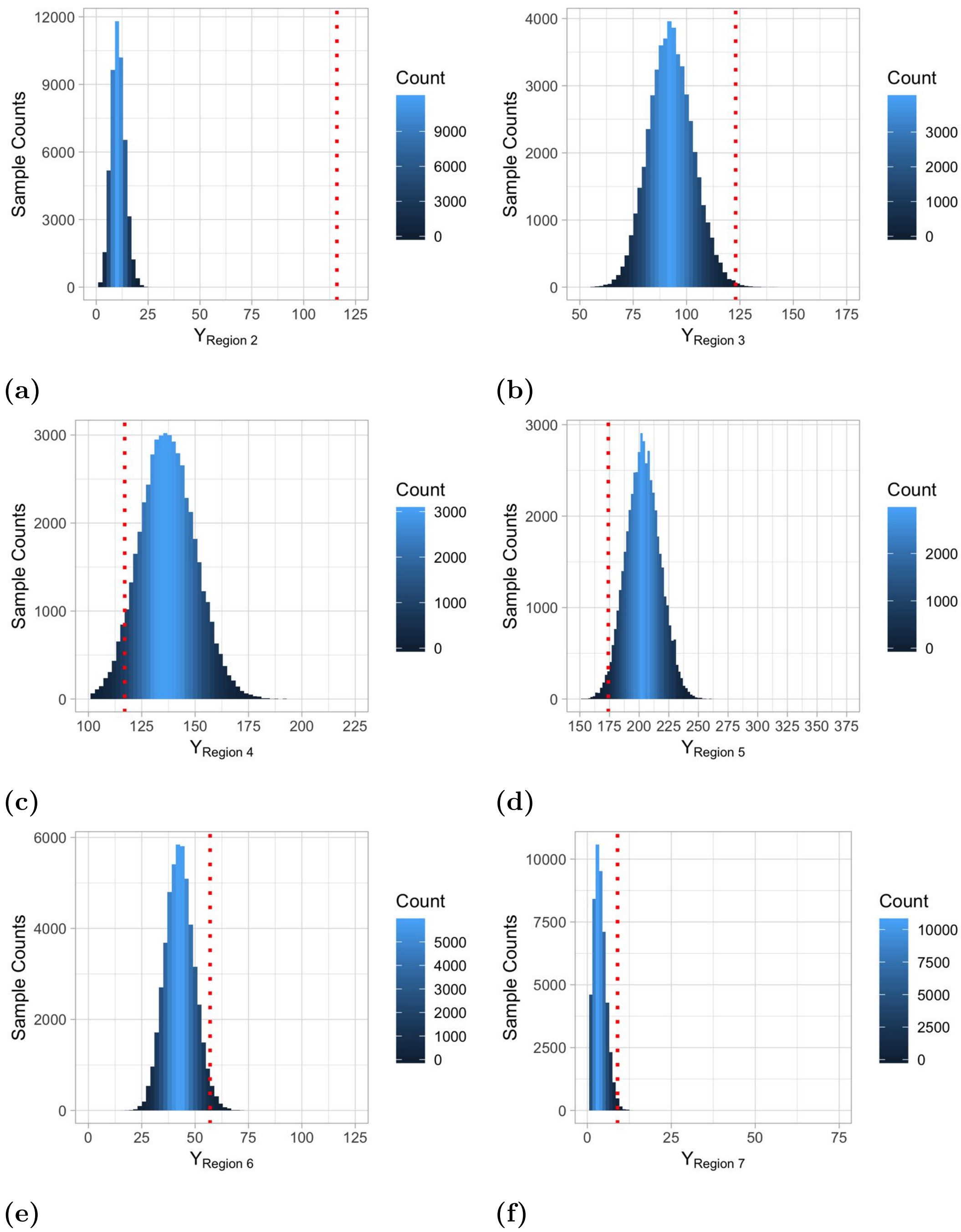
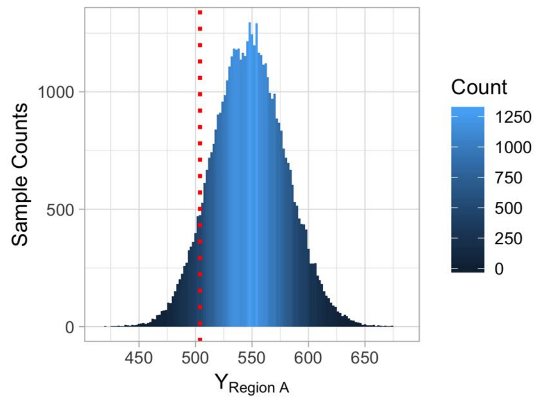


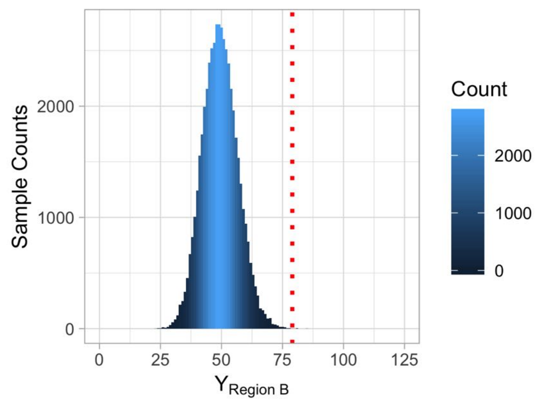
Figure 6.8: Histograms of TBCZs by 50,000 draws simulated from the posterior predictive distribution of Region 2 (a), Region 3 (b), Region 4 (c), Region 5 (d), Region 6 (e) and Region 7 (f).

climate, as well as more detailed consideration, such as hierarchical establishment.

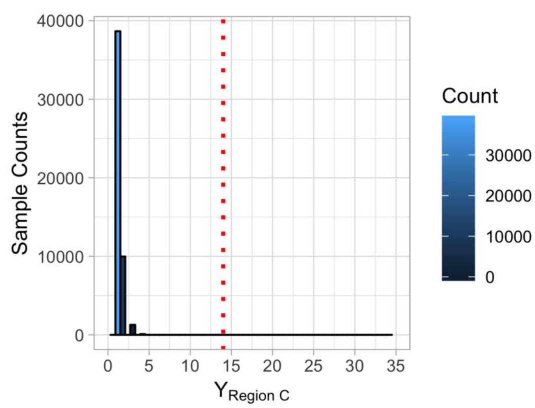
However, it is still intended to find a more robust understanding in a stochastic



(a)



(b)



(c)

Figure 6.9: Histograms of PBCZs by 50,000 draws simulated from the posterior predictive distribution of Region A (a) , Region B (b) and Region C (c).

way, as the output of the deterministic model is fully determined by the overall parameter values, i.e. $\mathrm{y_j}/\pi_\mathrm{j}$, which responds to a limited scenario rather that the phenomenon, which is death within this study. That is, the output of the stochastic model possessing some inherent randomness is needed to solve the degree of the impact of climate conditions on derailments in particular turnout systems, which are specifically chosen for this study due to the fact that they are of many engineering systems.

Figure 6.8[14] shows the approximation of a posterior predictive distribution (PPD) with an equal derailment parameter through regions, i.e. $\lambda_2 = \lambda_{\mathrm{j}}, \{j = (3,7), \mathrm{j} \in N\}$. In other words, the results of Eq. 6.8 and Eq. 6.9 are presented region by region in Figure 6.8. The PPDs might be useful to identify to what degree the estimates are appropriate, as the numbers of turnout-related derailment observations in all regions are also illustrated as red dotted vertical lines on the same plots.

6.3.2 Results of the stochastic model: response of the climates

Moderate climate regions, namely 3 to 6, seem to almost respond to the related assumptions and the function. For instance, the observations of Region 4, y_4 , and y_5 are placed near the middle of the predictive distributions. However, the majority of the other observations are in the tail portion of the distribution. Furthermore, the estimate for Region 2 is proved to fail rather evidently, which reveals that there is no absolute agreement of these observations with the fitted model. Therefore, regarding the histogram associated with the second region, it might be pronounced that the distribution of the samples needs to be focused on a higher range of observations (x axis) than simulated through the Eq. 6.7,

[14] The abscissa and ordinate of Figure 6.8 represent the number of derailment (y_j) and generated sample counts, respectively

based on an agreed value of λ. In Section 3 the US is said to be also separated through three regions, considering the characteristics of precipitation that the regions have. The results of these three regions are illustrated in Figure 6.9.

Similar to the harsh climate conditions in Figure 6.9, the estimate-distribution of the latter does not show the reality. On the other hand, although the number of derailments within Climate A is almost seven times higher than the other two zones, the observed number is placed on the left tail. Similar to Region 2 and Region 7 in Figure 6.8, it might, therefore, be concluded that the derailment counts of the three regions cannot be estimated properly and needs to be a hierarchical structure.

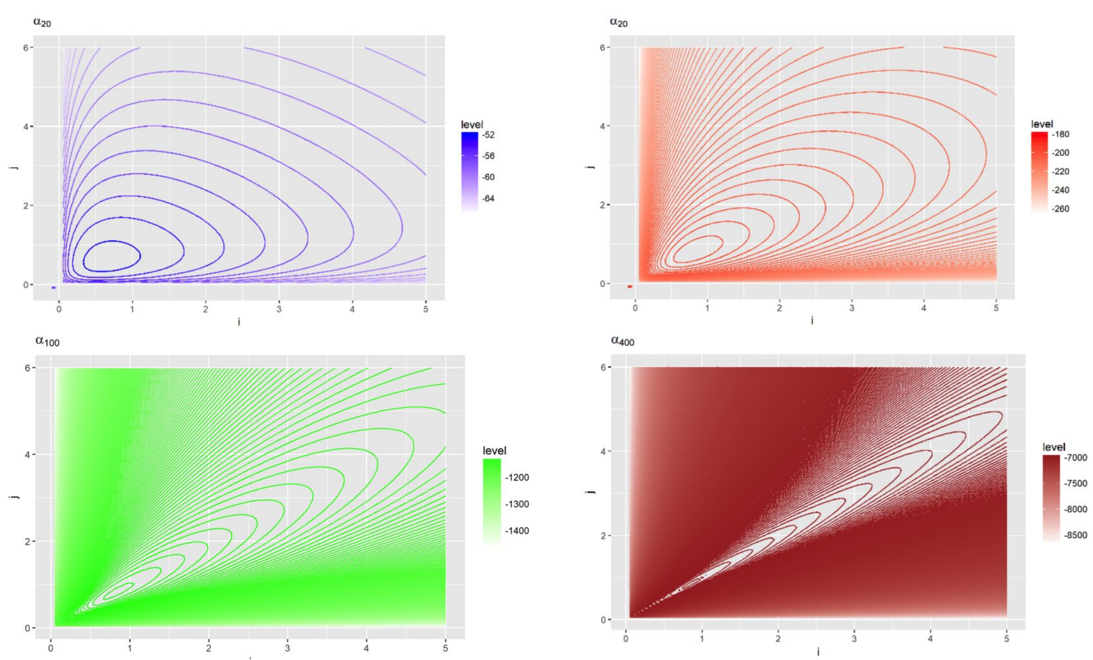


Figure 6.10: Behaviours of the exchangeable prior on $(\lambda 1(i), \lambda 2(j))$ against inverse gamma (alpha=10, beta= 10)[15]

[15]The Figure is based on the six temperature-based climate zones. The three precipitation-based zones are also calculated to find out final distributions, but as the hierarchical process of those is technically the same as done in Figure 6.10 to 6.13, only the temperature-based zones are shown so as not to repeat steps.

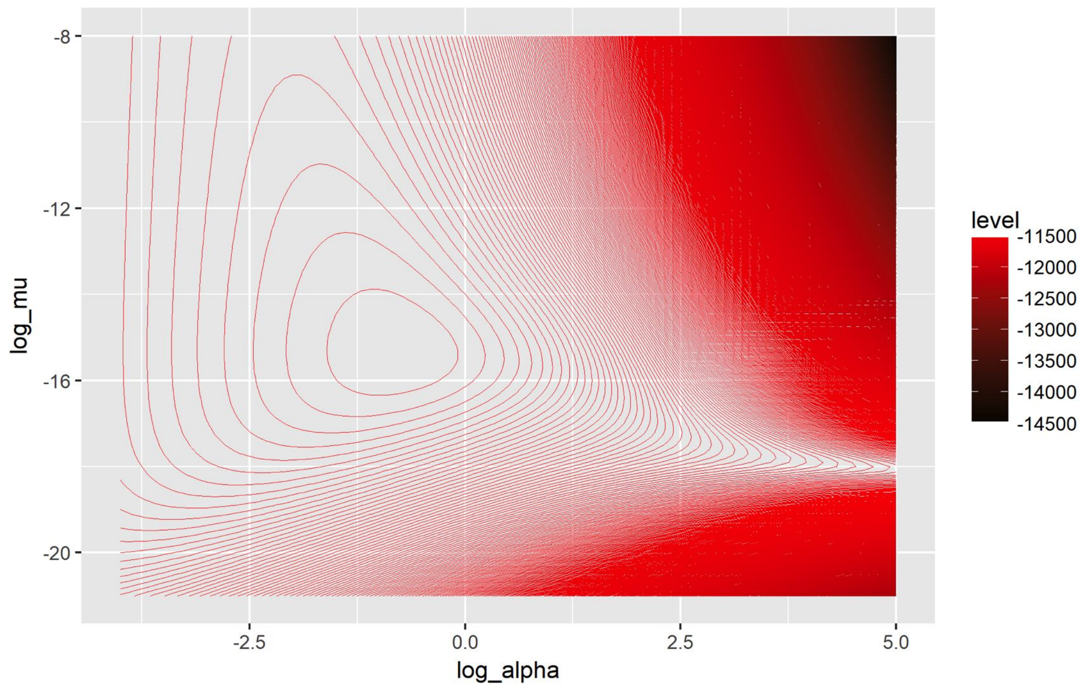


Figure 6.11: Behaviours of log (μ) and log (α) against US climate patterns

It is proposed by Eq. 6.9 that the most approximated rate parameter (π) of derailments through the regions could be derived from $\mathbf{g}(\pi| \propto_1, \mu)$. In order to achieve this a random sample of 50,000 is generated, which results in understanding the behaviour of the relationship between shape (α_1) and the mean (μ) parameters of the gamma function. As this study is designed on a priori hierarchical structure (see 6.3.2), both the generated sample and the relationship of parameters can only be reached in the event that the behaviours of hyperparameters, namely; $\propto_2$,a and b, which are nested at the second layer of the hierarchy, are revealed. In this circumstance, as $\propto_2$ is the only available hypermeter in the function, assigning random values on $\propto_2$ rather than the other two hyperparameters, has been considered to require less workload.

On the other hand, μ, one of the two parameters at the first prior stage, is assumed to follow an inverse gamma function with hyperparameters; namely, a and b equal to 10 (Albert, 2009). Thus, π_1 and π_2 can be fixed at a certain value, which leads to understanding behaviours of their exchangeable prior while $\propto_2$ changes. Figure 6.10. illustrates such behaviour when the unknown hyperparameter of an assigned inverse gamma function, $\propto_2$, is at 4, 20, 100 and 500.

In addition to these discussions, it might be stressed that each line of the distributions show an increment in the concentration of $\propto$. Therefore, the more $\propto_2$ values are assigned, the more λ_1 approximates to λ_2, and vice versa, which makes $\propto_2$ equal to infinity.

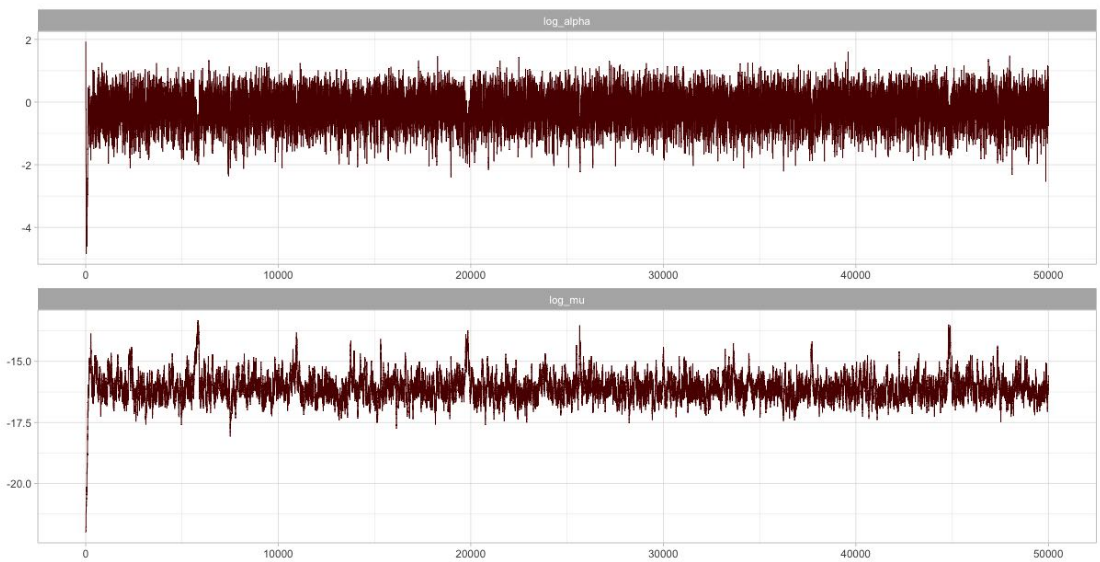
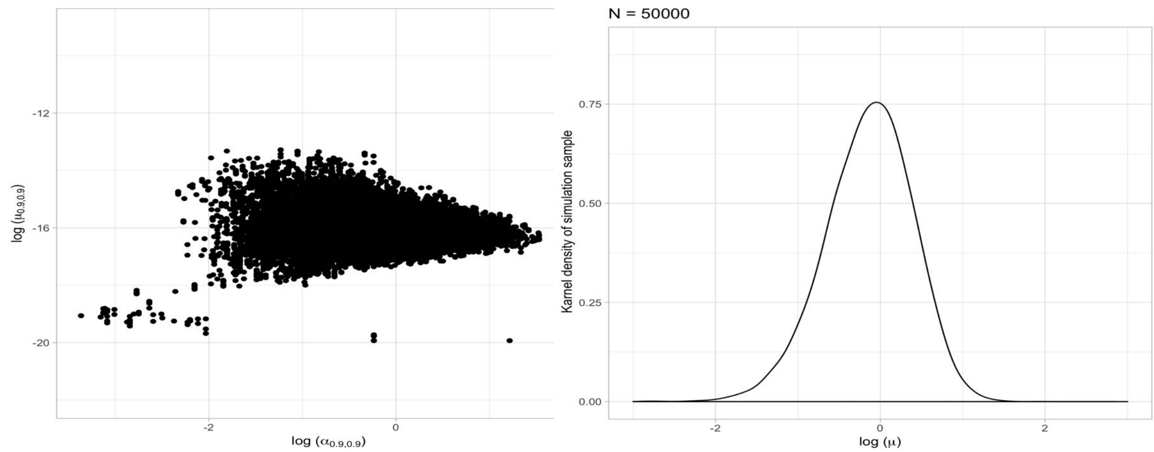


Figure 6.12: A representative trace of $\log(\alpha)$ and $\log(\mu)$ iterations of 50000 cycles through M-H algorithm [16]

There seems to be a centre around (0.95, 0.95). Prior density of the form is suggested (Albert, 1999) to be $g(\propto_2) =^{Z} / (\alpha_2 + z)^2$, providing that $\propto_2$ must be bigger than 0[17] . In this case, Z is assigned as 0.98. In addition to these discussions, it might be stressed that each line of the distributions show an increment in the concentration of $\propto$. Therefore, the more $\propto_2$ values are assigned, the more

[17] This is not because $g(\propto_2)$ but because of the behaviour of λ_1 and λ_2, as those would be undefined.



(a) **(b)**

Figure 6.13: A scatterplot of simulated values based upon the samples in the chain (a) and its density function (b)
by Metropolis -Hasting integrated in Gibbs Sampling

λ_1 approximates to λ_2, and vice versa, which makes $\propto_2$ equal to infinity.

These parameters and hyperparameters are also assigned with a sample of 50,000 randomly simulated from the joint posterior. $\log(\mu)$ and $\log(\alpha)$ are illustrated in accordance with the level of the posterior density in Figure 6.11.

The samples of $\log(\mu)$ and $\log(\alpha)$ are obtained through Eq.6.12 with a value of z, which has previously been found to be 0.98. To find out the centre of the lines, a plot with a long range of $\log(\mu)$ and $\log(\alpha)$ is performed, and then Figure 6.11 between $\log(\alpha)[|-3, 5]$ and $\log(\mu)[-21, -8]$ is selected to show straight-out the core of distribution. Figure 6.11 also illustrates the modal values through curving-alike red contour lines, each of which represents an interval of the logarithmic scale.

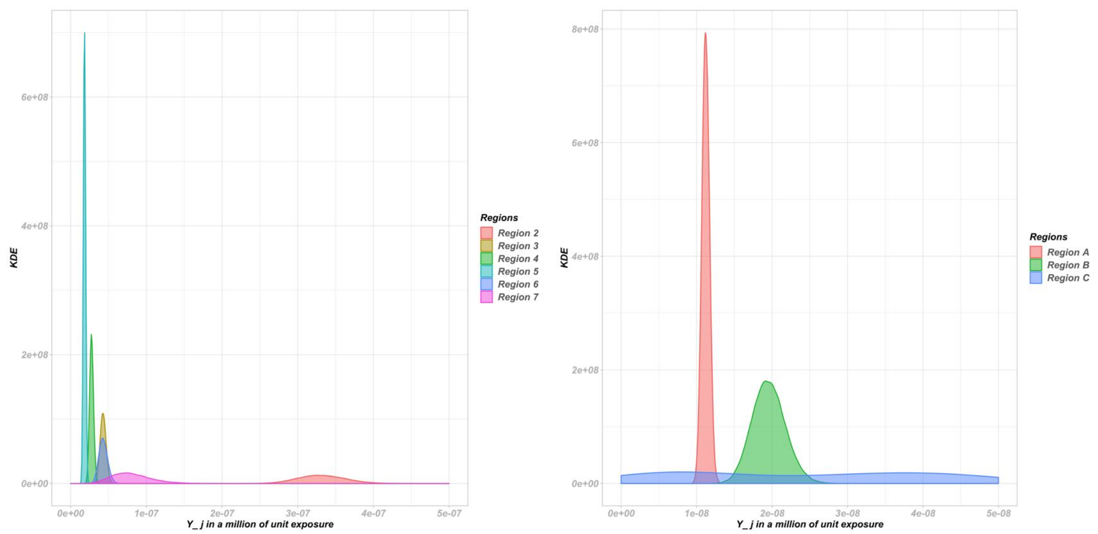
For instance, the 2 $^{\text{nd}}$, 4 $^{\text{th}}$ and 6 $^{\text{th}}$ lines from the core of distribution represent $0.1\%, 1\%$ and 10% of the modal value, respectively to assign a sample into the distribution, the function GIBBS , which is available in the LearnBayes package in R , is used. The function enables researchers to define an arbitrary real-valued posterior density into a Metropolis-Hastings merged with a Gibbs algorithm. Assignment of "start", one of the arguments under the GIBBS[18], might be seen as the starting value of the parameter vector in Figure 6.12. As noticed at first glance, the practice called burn-in is not used in this study since the nearby-real starting point is found to be earlier, which makes the technique an unnecessary part of this execution. The trace of the parameter vector seems to be well-distributed throughout the 50,000 different iterations of the chain.

The coordinates of points, composing the parameter vector and assigned by the MH algorithm, throughout $\log(\mu)$ and $\log(\alpha)$ are plotted out in Figure 6.13-a. The dog-tooth pattern indicates that the chain converged almost immediately, considering the distribution of log parameters in Figure 6.12. Figure 6.13-b shows the density of these samples, which indicates that most samples are generated, randomly near where $\log(\alpha)$ equals 1. There might seem to be some samples dispersed out of the dog-tooth. This is because of the nature of the MH algorithm, specifically assigned a fix "set.seed ()" function . The undesired samples, however, might be deduced to not impact on results as the longer tail of its density function, see Figure 6.13-b, places it at a relatively low level due to the large size of the generated sample.

The main point of this investigation by real cases is to provide the required response to the question as to whether characteristics of a climate regime manipulate annual derailment counts at railway turnouts. It has been attempted to level out all covariates, such as π, e, λ throughout the chosen regions. After some assumptions, see Sec.2, this theoretically brings out the ultimate outcome of the entire endeavour, shown in Figure 6.14.

[18] Usage: gibbs (logpost,start,m,scale,...). Logpost, start, m, scale are assigned as Eq. 6.12, start = c (2, -22), 50,000, c (1.00, 0.25), respectively. For further details see; https://www.rdocumentation.org/packages/LearnBayes/versions/2.15/topics/gibbs.

Essentially, Figure 6.14 illustrates the density functions of nine chosen climate regions as the derivative of the Eq. 6.6 throughout a continuous distribution of 50,000 samples per each region. The areas that are covered under these curves, produced by the density functions and the x- axis, are equal to 1. On the other hand, the Y axis points out not absolute counts, but relative frequencies of the curves.



(a) **(b)**

Figure 6.14: Regional posterior density functions of derailment at railway turnouts in a year for TBCZs (a) and PBCZs (b)

In Figure 6.14-a, three distributions, associated with Regions 3 to 6, are observed to behave in quite similar manner to each other. Considering that the first region is left out of the research for several reasons, Regions 3, 4 and 5 have, in fact, more moderate climatic conditions through the year than the others. As a result, this common behaviour could be expected. As for Region 6, covering the large northern US, it is observed that this climate tends to approach Region 7 by diverging the three moderate regions. Even as the climatic characteristic of Region 6 is already known (see 6.2.1.3), it is now revealed that a light impact of these characteristics on derailment counts, Y_6, presents. However, this hypothesis could be open to discussion, considering that this study has not dealt with the distribution of operational error. For instance, maintenance, as an operational error, has recently been found to have been involved in 20% of all turnout-related derailments inthe UK(Dindar et al., 2018). Operational error on railway turnouts in the US is still an unknown phenomenon. This study can be extended by working on operational error. It can be considered that the distribution of such errors might be considered to disperse quite uniformly across the US railway network at the rate of relative areas that are covered by regions. It should not be forgotten that these assumptions might result in outcomes that are not able to deduce an absolute meaning. Therefore, nothing can be said directly about Region 6. Instead, the general characteristics of a cold region are likely to impact on the derailment counts in the region, considering that the yellow line starts to resemble the brown line in Figure 6.14.

On the other hand, the regions in which extreme weather conditions prevail, namely, Region 2 (red line) and Region 7 (pink line), show explicitly different patterns from the others. The first striking feature is that both regions take a place on the right side in a discrete way.As a certain result of this, it can now be pronounced that the extreme weather conditions [19] impact on component failures for railway turnouts, causing derailment, even though it does not present verbally on official reports [20].

[19]The phrase is, in general, used to express weather events that are significantly different from the usual or average weather pattern taking place over a period of time. The research refers to seasonal adverse conditions of the US‘s average weather pattern.

[20]Official accident reports, in fact, mention environmental reasons, covering codes beginning with “M”, such as M102, Extreme environmental condition - TORNADO. This paper has not attempted to discuss such deterministic explicit reasons, but investigation of climate impacts on component failures for railway turnouts on a stochastic methodology has so far been a milestone for railway researchers to understand the real climate impact beyond observable facts.

The karnel density function (KDF) of Region 7, covering cold regions, is seen to be placed in a long range of Y_7 values. This behaviour of the density function stands for a lack of preciseness in the estimate, as the density function reacts instinctively to fulfill a real Y_7 value, due to insufficient knowledge, compared to the others. The study investigates 596 derailments across the US over the five years from 2010 to 2015. It is observed that a range of roughly 70 to 90 derailments is distributed throughout five climate regions, while Region 7 has a population of under 50 derailments. Therefore, the KDF function of the coldest region seems to be dispersed. However, the median value of the KDF is seen to take a place in-between the values of moderate regions and Region 2.

The sample distribution of Region 2 is seen to have the most distinguishing features. As an abundance of data provided by the region is enough, a distribution with a higher mode and median than Region 7 is observed. Moreover, the KDF is the highest median of all. In light of these findings, it is mathematically possible to claim that the more extreme environmental conditions a region has, the more component-related failures railway turnouts of this region possess.

The KDF of precipitation-based climate zones, on the other hand, is shown in Figure 6.14-b. Similar to the results of the KDF of TBCZs, the more derailment observations, a better estimate can be conducted. Fourteen cases are observed to have occured across Zone C, which is shown with blue colour. Although the peak of KDF is around 3^{-6}, it is almost impossible to make a comment on the precipitation regime of zone 3. This is highly likely to be due to a low number of derailment cases and negligible exposure compared to the other two regions. The green-coloured distribution, Zone B, which is moist, visualises the distribution of derailment (y_j) probability over a million of (e), which is lower than Zone B, where a dry climate prevails.

The blue coloured distribution, Zone B, which is moist, visualises the distribution of derailment (y_i) probability over a million of (e), which is higher than Zone B, where a dry climate prevails.

6.3.3 Robustness of the model for component failures at RTs

It is assumed that the derailment rates were sampled from the gamma function, see Eq. 6.9, with two parameters ($\mu and \alpha$). While a non-informative prior proportional to $1/\mu$ was assigned to μ, $z_0/(\alpha + z_0)$ was assigned to $\propto$. Z and is assessed as 0.98 for this study. Figure 6.15 shows prior and posterior results by the chosen value of z (0.98) and the testing value of (98).

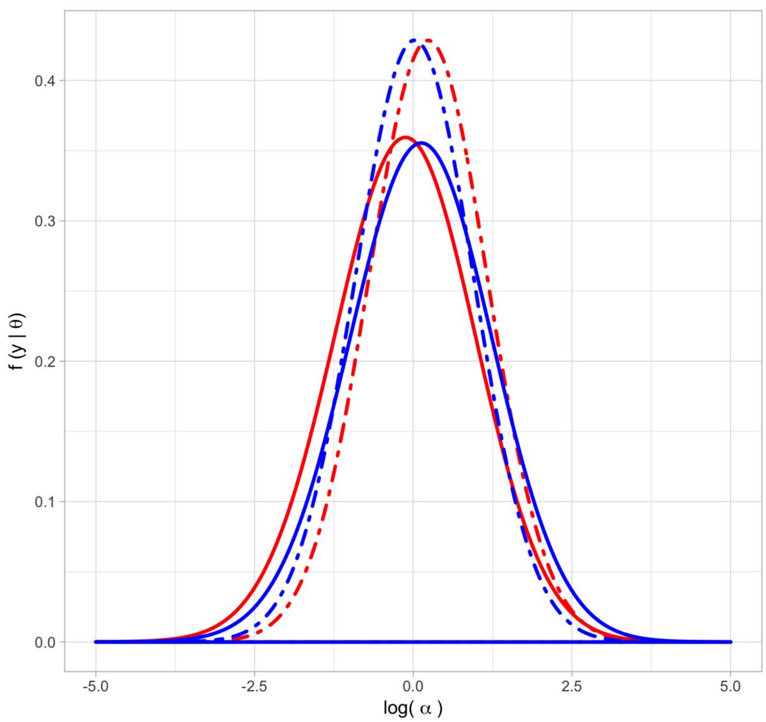


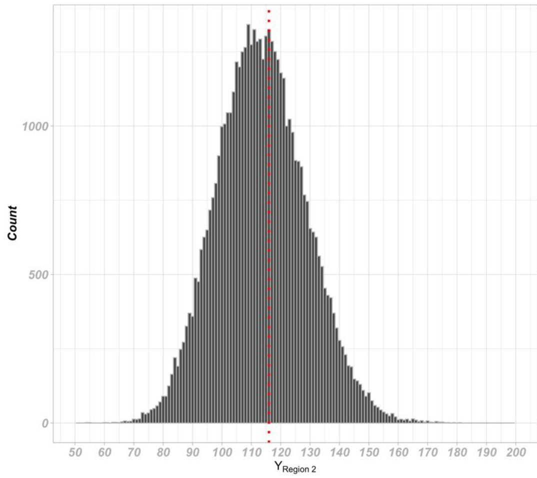
Figure 6.15: Posterior (solid lines) and Prior (dot-dashed lines) Density Functions for TBCZs.

These prior (red lines) and posterior (blue lines) functions are shown in Figure

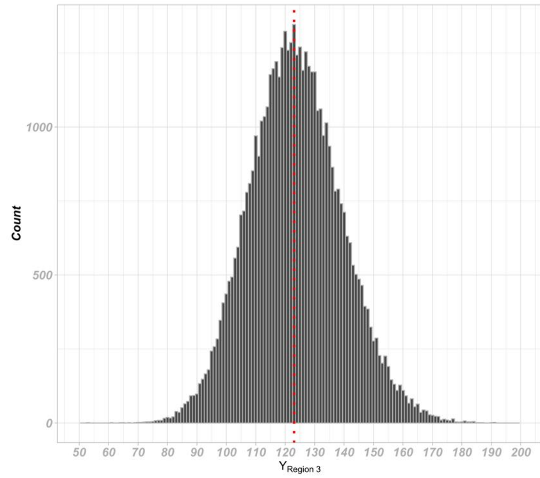
6.15. The y-axis of the Figure illustrates the density of samples while the x-axis of Figure 6.15 gives an idea on $\log(\alpha)$. Dotted lines denote posterior functions, while blue lines are obtained through an increased z value. It is seen that the assumption ‘z‘ does not impact largely upon the prior and posterior functions, even though the z value is increased by 100 times. In other words, the z value does not seem to be largely effective, which shows the robustness of the model.

As have been seen in Figure 6.8, Y_i values of climate zones 2 and 7, which are relatively extreme hot and cold respectively, have been shown to reveal how effective is one layer of the derailment estimate. Moreover, the estimates (bar chart) have not been observed to not satisfy, considering a real number of derailments in a given time (red dot line) in this Figure 6.8. As a result of hierarchical modelling and the preciseness of exchangeability of π_i, ultimate estimates are expected to be better than found previously. In contrast, the estimates for climate zone 2 and 7 (of TBCZs), illustrated in Figure 16-a & Figure 16-b, respectively, yields better estimate. Taking into account that the distribution of the derailment estimate for zone 7 on one-layer structure did not meet the real count, the distribution in the hierarchical structure seems to be placed in a desired way. On the other hand, the worst estimate has been seen on the second zone. It is now confidently pointed out that the hierarchical structure gives a risk analyser an opportunity to estimate.

The estimate of the hierarchical model for PBCZs is illustrated in Figure 6.17 In order to visualise whether or not the distribution of samples by the suggested hierarchical model better estimates, Figure 6.17 might be compared to Figure 6.9. One layer modelling has given the histogram as placed on the far-left side of $\mathbf{y_A}$ (the number of real observed cases). However, $\widetilde{\mathrm{y_A}}$ is seen to be placed properly at the middle of the distribution in Figure 6.16.



(a)



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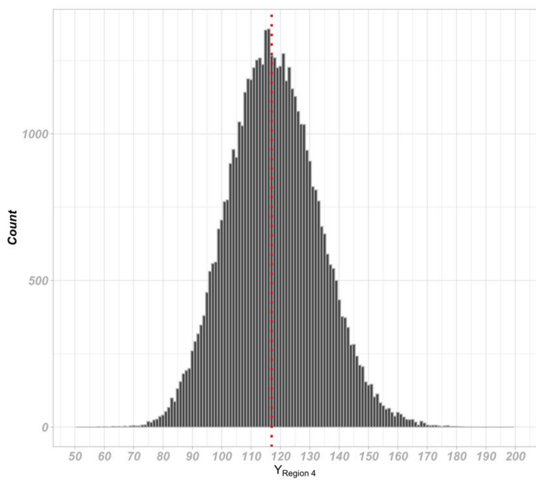
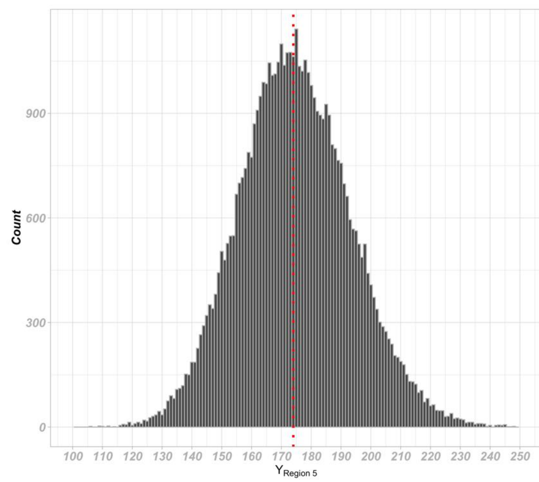


(c)



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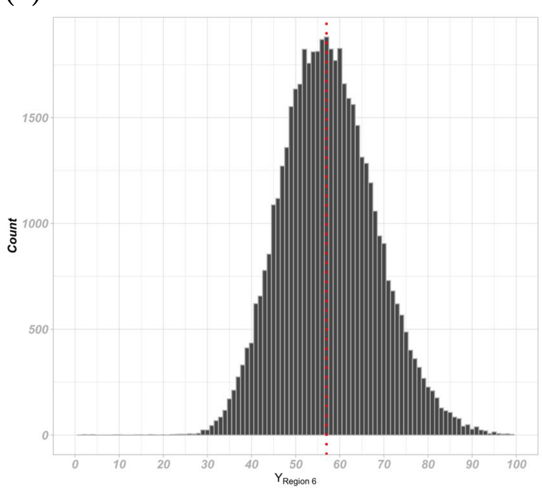

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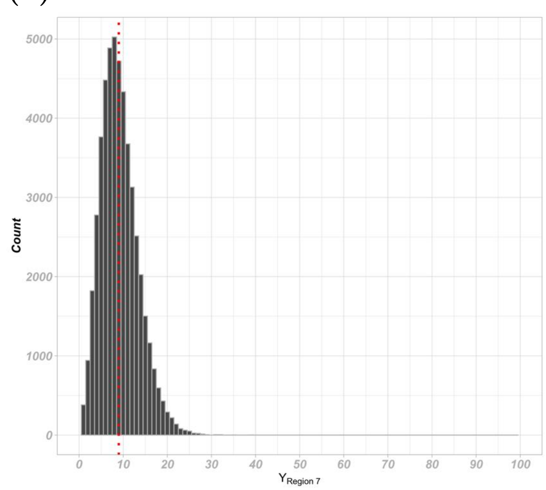
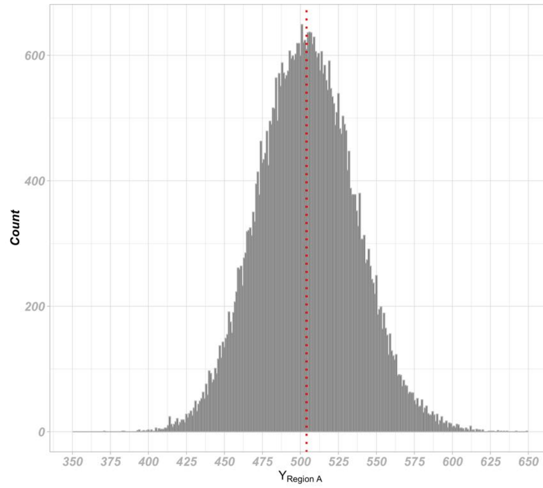
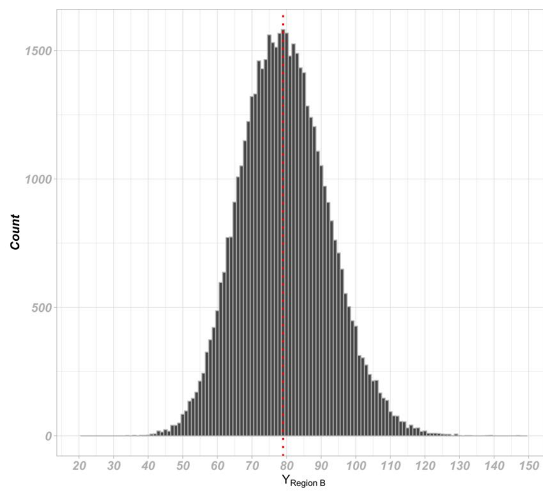


(f)

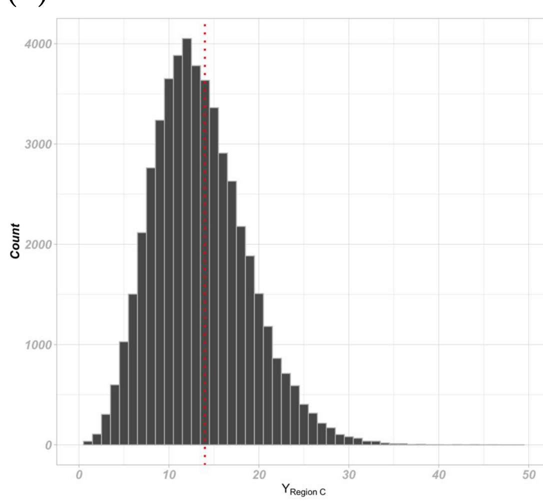
Figure 6.16: Histograms of TBCZs by the posterior predictive distributions of Region 2 (a) , Region 3 (b), Region 4 (c), Region 5 (d) , Region 6 (e) and Region 7 (f) from the hierarchical model.



(a)



(b)



(c)

Figure 6.17: Histograms of PBCZs by the posterior predictive distributions of Region A (a) , Region B (b) and Region C (c) from the hierarchical model.

6.4 Discussion

Railway safety and risk analysis are reliant on precisely estimating derailment rates along with a thorough comprehension of the factors that influence such incidents. The purpose of this study is to enhance the identification process of both in the context of derailments connected with turnout constituent failures when presented with significant volumes of official information. To achieve this, a hypothesis is made in terms of environmental considerations, such as temperature and precipitation, and their subsequent effects on derailment frequency in regard to turnout constituents. Thus, the contiguous United States, excluding Hawaii and Alaska, is separated into seven distinct regions on the basis of temperature (climate regions 1 to 7) and three distinct regions on the basis of precipitation (climate regions A to B).

The particular levels of exposure of the zones are specifically examined and determined, which are labelled as railway traffic density (MGT) and the volume of turnouts throughout each zone. A hierarchical Bayesian model is applied for the purposes of arguing the hypothesis, due to the fact that it is presumed that a Bayesian model composed of only one layer is not able to give the appropriate response as a result of the environmental considerations, which additionally provides the possibility of testing them against each other. This is believed to demonstrate the accuracy of the research. It is identified that a total of 596 incidents of derailment were recorded throughout the United States in the past 5 years as a result of different turnout constituent breakdowns. In order to explain the derailments, the specific levels of exposure in the climate regions, which are affected by railway traffic across every turnout, in addition to the amount of railway turnouts, are determined on an individual basis for each of the nine selected climate regions. Initially, the results are displayed via one layer of Poisson distribution, which is generally the preferred method within the railway sector (Liu, 2017). Subsequently, a hierarchical Bayesian model is utilised. Thus, a comparison is made between the findings generated by the two distinct statistical methods and the volume of recorded derailments (actual counts) in each of the climate regions to ascertain which estimate has the best fit and to what extent each of the approaches reflects the real situation.

It is determined that the hierarchical model produces more effective outcomes, specifically in situations where the data is scarce (i.e., reduced rates of derailment or exposure). This is because the estimated distribution of PBCZs within Zones B and C (low derailment rate zones) are not regarded to be correct estimations in the absence of a hierarchical model. After updating the distributions via the hierarchical model, it is shown that the amount of perceived derailments is located within the revised distributions of Zone B and C.

In other words, the volume of recorded derailments in the extreme climate regions is found be in accordance with the derailment incidents using the fitted hierarchical Bayesian model. Conversely, the posterior predictive distributions (PPD) of PBCZs and TBCZs assess the suitability of Albert‘s exchangeable hierarchical Bayesian model with particular levels of exposure so as to determine the verifiable derailment frequencies for every selected climate zone. As a definite outcome, the behaviour of this phenomenon is observed to differ throughout the region. More precisely, the zones characterised by extreme weather patterns exhibit largely homogenous rates. For example, the PPDs associated with climate regions 3-5 of TBCZs are found to be located close to each other on the axis, which represents y values in million exposure units. Contrastingly, it is likely that the remaining TBCZs, which are defined as extreme climate zones for the purposes of this study, will be described as zones that present considerable risks in terms of derailments caused at turnouts. It is seen that these zones experience derailments at a rate that is several times more than zones that are characterised by more moderate weather conditions. Due to the fact that regional exposures, taken from the total traffic volume and the amount of turnouts in the zones, are allocated to the same unit, the assumption could be made that other factors could be influential, such as differences in maintenance processes, track condition and distinct methods used to report incidents of derailment.

Nevertheless, all derailments are selected based on the same class of track in the FRA reporting, which has formal jurisdiction over the quality of track as a result of the authority assigned to it by the Railroad Safety Act of 1970. Hence, in terms of the selected incidents connected to turnouts, one could claim that both the overall standard and layout of turnouts have similarities throughout the United States. Even though one could debate this assertion, it is possible that the turnout properties are distributed homogenously, given that a significant volume of turnouts are functioning across the railway network in the United States. In terms of track inspection, this is the responsibility of both the FRA and the railway operators themselves. While certain operators are in possession of proprietary detection equipment, most Class 1 systems retain their own engineering vehicles, which are utilised for the routine monitoring of a broad scope of aspects that are crucial for maintaining operational safety, establishing a profile of a variety of constituents, alignment and gauge. The rate at which turnouts are inspected can be categorised into two groups: “main track” or “other than main track”. It can be seen that the frequency of incidents involving derailed trains on main track is very low. Hence, the inspection frequency of the turnouts connected to such derailment events, which are the focus of this study, must have been similar.

Thus, the unique properties of the segregated zones appear to be the primary cause of the considerable differences in derailment frequencies. The research indicates that there is a significant correlation with climate regions and derailment frequency. Similar to the expectations, certain weather patterns, such as severe cold and hot conditions in addition to moisture, are seen to have major effects on the frequencies. Considering derailment rates per exposure, climate zones 2 and 7 of TBCZs are determined to fold in two and three to the mean of the other zones, respectively.

Furthermore, sample distributions of the zones, apart from these two, are identified to have overall similarities to the hierarchical model. In other words, it is determined that regions characterised by mild climates, namely climate zones 3-6 of TBCZs, do not have the same level of impact on derailments caused by constituent failures in severe climate regions.

6.5 Conclusion

Chapter 3 identified component failures to be responsible for the majority of derailment causes. Therefore, it is an essential task for the thesis to analysis, monitor and manage component failures-oriented risk. Chapter 6 provides a novel risk management methodology, which is established to cope with component failures causing derailments at railway turnouts. As a result of findings represented in Chapter 2, this novel framework is designed through a stochastic process due to scarce data environment. In other words, a stochastic model established on M-H algorithm is proposed to identify and rank the risks of various phenomena causing derailment through component failures. The proposed model has the capacity to cope with uncertainty in the inputs, as the behaviours of hypermeters in the hierarchical are unknown. Responding to the regional segmentation of Chapter 4, Chapter 6 splits the entire railway network of the US into seven temperature and three precipitation zones. The results are compared with the real observation, and are found to be applicable to railway operation, as the estimates are quite close to real observations. On the other hand, the performance investigation of this novel proposed risk management framework for railway turnout components over the existing assumption based frameworks is left to the next chapter.

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CHAPTER 7

RAILWAY ACCIDENT ANALYSIS USING LARGE-SCALE INVESTIGATIONS OF TRAIN DERAILMENTS ON SWITCHES AND CROSSINGS

7.1 Introduction

Derailments occur in situations where a train vehicle loses stability and is dislodged from the rail, which could be caused by a variety of different factors, including mechanical defects of turnout constituents, such as defective turnout crossing noses. When conducting prediction analysis for these parts, it is common practice to apply GIS and Mathematical modelling. In comparison to GIS, which was first introduced for the analysis of train-related accidents in the early-2000s, mathematical modelling for accidents is relatively developed in the field of transportation engineering.

The first case in which railway accident frequencies were mathematically studied in a comprehensive manner was the study by Nayak et al. (1983). This research focused on holistic derailment frequency as well as the probability distribution of the amount of wagons and train engines within the United States. The estimation methodology involved in this process has been revised through various subsequent studies, thus producing more specific methodologies with greater sophistication. A quantitative association between derailment rates and class of track has been determined, which takes into account traffic density as well as the place and frequency of the derailment incidents (Treichel and Barkan, 1993). A different study has allowed the likelihoods of Class I and non-Class I railroad goods train accidents to be calculated with increased accuracy for the different categories of main-line track (Anderson and Barkan, 2004). Essential parameters have been disclosed by using the US Federal Railroad Administration (FRA) accident database as well as associated studies in the literature, which were then examined to provide a prediction of the derailment of train vehicles (Anderson and Barkan, 2004). The same researchers (Liu et al., 2017) additionally considered track classes designated by the FRA, the operational methods, and yearly density of traffic in the process of developing both point estimators of and confidence intervals of rates of derailment. Dindar et al. Dindar et al. (2018b) designed a Bayesian mathematical model that can be used in the identification of derailment risks resulting from severe weather events. The basic agreement between these studies in terms of derailment rate estimations represents an exhaustive methodology that can be employed in the estimation of a variety of different types of defects that cause derailments. Due to the fact that both railway safety and risk analysis are dependent on the ability to precisely assess the probability of derailment, as the accuracy of the estimation of derailment volume increases, the costs associated with maintenance may decrease and a higher level of overall railway safety can be achieved across the network.

GIS is a widely used technique for enhancing the safety of railway networks as well as for the identification of a weighted mixture of the risks and costs related to derailments for a group of reasons. A study was conducted on the trade-off between cost and risk for the railway transportation of dangerous goods so as to uncover various rerouting challenges in which the railway network was overlaid on a census area map utilising a GIS approach (Glickman et al., 2007). A quantitative risk analysis of dangerous goods has been developed on the basis of GIS for the evaluation of tank car design, product properties, traffic density, condition of infrastructure, and the exposure of the population adjacent to transportation paths (Kawprasert and Barkan, 2009). The optimum rate of inspection for distinct track sections has additionally been established by utilising GIS to precisely ascertain the route data for every rolling stock (Liu, 2017). The effects of weather conditions on constituent defects at railway turnouts (RTs, also known as ‘switches and crossings’) have been examined through the application of GIS to estimate the exposure compounds (see previous Chapter).

Generally, mathematical models integrated into the methodological approaches of quantitative risk research could be complemented by certain presumptions, where some are comparatively more heuristic. The data properties, such as the relational patterns, spread, and kinds of variables, are usually governed by these presumptions. In research focused on railway risk, numerous studies have established certain presumptions, specifically those associated with a group of risk indicators (e.g., railway traffic) for the purpose of duplicating the proposed research situations with high levels of similarity (Dindar et al., 2017a, Ishak et al., 2016). The underlying basis for these presumptions is founded on statistical information that has a certain level of correspondence to the studies. Hence, study population, statistical tests employed, design of the research or additional study delimitations have an increased likelihood of developing ambiguity among readers.

This chapter examines the extent to which these common presumptions effect the anticipated outcomes, irrespective of the GIS approach employed. In order to achieve this, a zone is divided considering the weather patterns, the purpose of which is to remove any effects of weather. For the analysis of specific derailments associated with turnout constituent defects, the degree of exposure in every state inside the divided zone is ascertained based on actual data and/or a series of presumptions. Lastly, by comparing the results for various degrees of exposure, the rates of derailment are ultimately calculated through the application of a hierarchical Bayesian model (HBM).

Overall, this Chapter is profoundly established to verify the novel methodology of the Chapter 6 in comparison to prevailing approaches in the literature. Hence, this will allow readers/railway operators to determine a precise answer to deal with component failures as a result of environmental impacts(contributory factor).

7.2 Method

7.2.1 Data reliability and use

The US Department of Transportation has given officially authority to the FRA to keep official records and produce records on a variety of different kinds of accidents, including those involving collisions and derailments, on the basis of the regulations stipulated in Title 49 of the Code of Federal Regulations (CFR) Part 22. The FRA analyses the aforementioned reports to distinguish relative patterns with regard to safety on railway networks as well as to establish programmes aimed at reducing derailment risk and eliminating derailment hazards in order to prevent the occurrence of casualties and incidents on the railways. One of the most frequently occurring types of accident/incident included in these reports is related to railway equipment. The different groups of accidents observed will be assigned numbered codes for the purposes of this study.

This research examines the failure of RT constituents, which are categorised according to the FRA codes T301 – T399. As can be observed in Table 7.1, the FRA has divided constituent failures related to RTS into 18 different accident categories, where each explains distinct RT failures and causes a variety of outcomes.

It is recognised that RTs are significantly impacted by environmental factors, such as temperature (Dindar et al., 2016, Saadin et al., 2016). Consequently, it is assumed that the physical transformations that occur in turnout constituents will differ depending on the climate zone. Hence, it is proposed that segmenting the zones based on weather properties could produce improved estimations (Dindar et al., 2018a, 2017b,c). Due to the objective of this chapter (examining the vali-

Table 7.1: Reported Failures of crossing noses, switches, and track appliances at RTs.

FRA Code	Failure Description
T301	Derail, defective
T302	Malfunction or failure of expansion joint
T303	Mislocated or dislodged/broken guard rail
T304	Wearing or breakage of railroad crossing nose
T307	Malfunctioning spring/power switch system
T308	Wearing, breakage or disconnection of stock rail
T309	Broken, loose or fatigued switch (manual) stand system
T310	Defect or breakage of switch linking or functioning rod
T311	Damage or misalignment of switch
T312	Breakage of switch lug/crank
T313	Misaligned switch due to inadequate rail anchoring
T314	Wear or breakage of switch point
T315	Wearing, bending, breakage or disconnection of switch rod
T316	Wearing or breakage of turnout crossing nose (rigid)
T317	Wearing or breakage of turnout crossing nose (self-guarded)
T318	Wearing or breakage of turnout crossing nose (spring)
T319	Switch point gapped (between switch point and stock rail)
T399	Additional defects in crossing nose, switch or track equipment

dation of the proposed structure in the Chapter 6), the removal of the effects of climite itself may be required. Figure 7.1 illustrates the climate zone distribution throughout the United States.

The United States is comprised of seven basic temperature-based zones (TBZs) as well as three precipitation-based zones (PBZs). TBZs are assigned numbers from 1 to 7, whereas the PBZs are divided into three categories: A to C. Every zone possesses distinctive variables, like precipitation, temperature, density of railway traffic as well as class of track, which is considered an intersectional variable. For the purposes of the present study, a region comprising TBZ 4 and PBZ A is used,

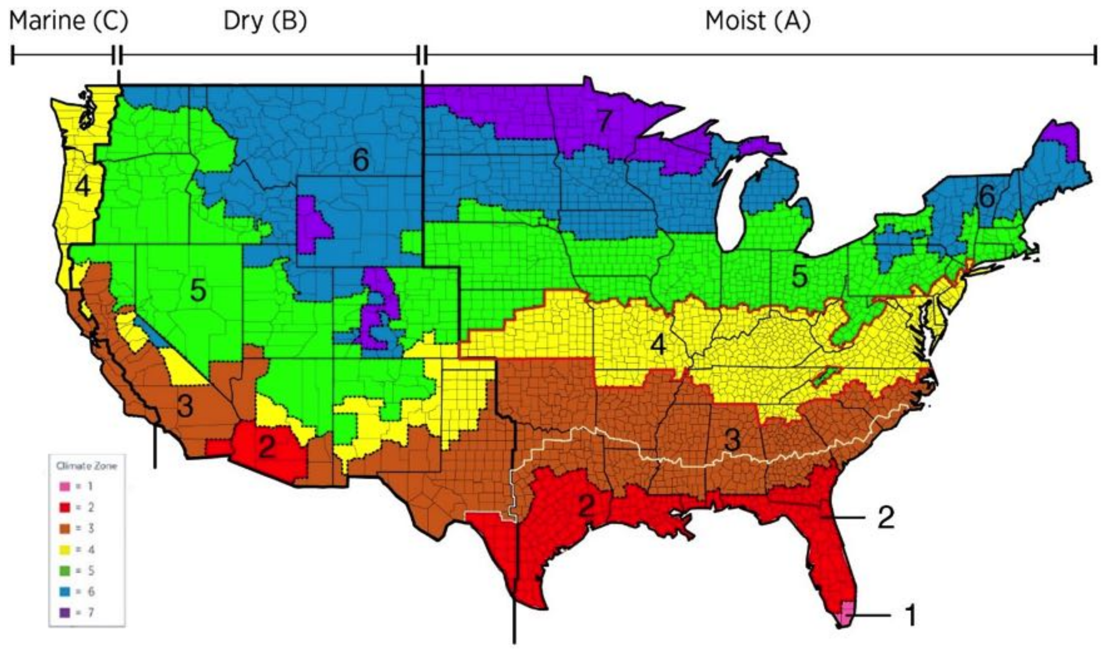


Figure 7.1: Climate zones in the US

which is coloured yellow, bordered by a red line and located on the right side of Figure 7.1. As previously stated, this particular zone has been selected in order to reduce the effects of weather. The US states contained within region are Arkansas (AR), the District of Columbia (DC), Delaware (DE), Georgia (GA), Illinois (IL), Indiana (IN), Kansas (KS), Kentucky (KY), Missouri (MO), Maryland (MD), North Carolina (NC), New Jersey (NJ), New York (NY), Ohio (OH), Pennsylvania (PA), Tennessee (TN), Virginia (VA), and West Virginia (WV).

The interconnect railway networks within the contiguous United States comprise a total of around 140,000 miles of track, and the responsibility for completely overseeing the condition of the networks falls on the FRA and railway operators. Tracks are grouped into six categories, which are indicative of the track quality and are divided on the basis of speed restrictions. This research will focus on estimating derailments and their seriousness based on the individual states for the whole network system in the selected area. The assumption is made that the state of the turnouts is spread in a homogenous manner across the states, as the research purely focuses on derailments on whole tracks. Nevertheless, it is stated that the volume of homogenously spread turnouts within a state has relevance to either the total length of the railway network or the traffic density (rail ton-miles per track mile per year[1]). While the former could produce unfeasible outcomes by taking into account the potential for different turnout counts as a result of the size of the network, this study is inclined towards the utilisation of both the former and latter, which would provide more realistic data in regard to the extent to which turnouts throughout the whole network are exposed to all types of rolling stocks even under presumptions. Apart from the measure of railway traffic within this zone, the assumption is made that the turnout count has a homogenous distribution. It is deterministically identified that one turnout exists[2] for every 1.18 mile of track (see Chapter 4) (Dindar et al., 2018a).

With respect to the actual traffic density, a traditional approach used by the majority of the railway sector for the measurement of railway traffic across a stretch of track is MGT, which is determined by utilising ArcGIS. As this study purely concentrates on turnouts (or 'switches and crossings'), the railway traffic travelling over a turnout (rather than a portion of track) is utilised in the calculation of railway traffic based on MGT. Hence, the measurement of the MGT of traffic is made on the basis of the cumulative overall static weight (inclusive of wagons and locos) of the traffic traversing a turnout annually. MGT will be employed as a unit of actual data as well as an assumption, which facilitates the process of directly comparing actual data with data that has been generated

[1]This is the produce of the year overall weight (inclusive of both locomotive and full/empty wagon weights) and the distance that a train vehicle travels

[2]The turnout count is estimated by only taking into account the volume of switches in a section of rail. For example, a single crossover comprised of two switches is defined as two turnouts situated on two tracks.

mathematically. Conversely, the carloads measure, which is solely utilised for an assumption, is acquired based on the count of cars that traverse the turnout loaded with freight. Furthermore, rail ton-miles are also utilised for the assumption of exposure in the separated areas, thus representing the whole selected region. This an additional railway traffic unit and can be equated to the shipment of one ton of goods per one mile without taking into account any different type of static weight, like those of the engine and wagon. Comparisons will be made between both rail ton-mile and carloads and MGT to assess how they can be utilised to approximate derailment counts.

7.2.2 Structure of Methodology

The overall study is outlined in Figure 7.2, which indicates that there are three technical stages. The wider objective is initially to acquire derailments from a variety of different data resources through the application of diverse mathematical modelling approaches. Subsequently, comparable statistical analysis is conducted to provide a benchmark for the determined derailment rates.

To facilitate the accomplishment of the research goals (identifing the performance of the proposed study in Chapter 6), a stochastic procedure as a mathematical object is utilised. This is an innovative mathematical procedure utilised in the identification of the derailment rate distribution at a particular point in time using random variables, as opposed to a deterministic procedure found on derailment numbers, traffic density and railway turnout counts. The sources of data, namely real quantitative data (RQD) and presumptions, are detailed in the following subsections. The initial three mathematical presumptions (A-1, A-2, and A-3) are related to distinct railway traffic units (million gross tonnes (MGT), rail ton-mile, and carloads, respectively), whereas the fourth presumption (A-4)

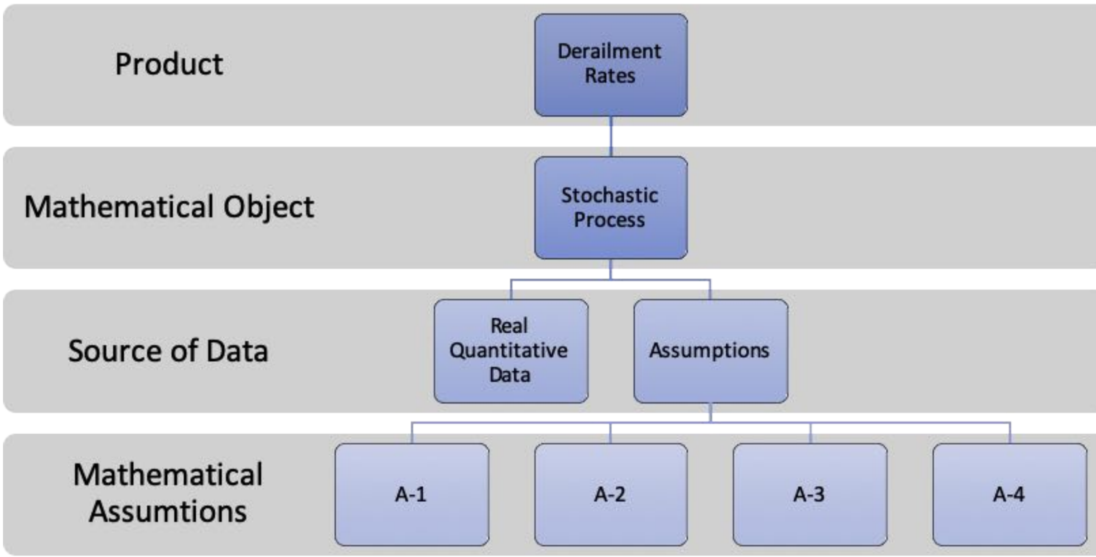


Figure 7.2: Research phases

denotes the turnout count, which is an additional indication of risk.

7.2.3 Indicators of Exposure

The exclusion of environmental influencers is achieved by segmenting the states based on weather trends. Due to the fact that both railway traffic density and turnout counts in each of the divided states are taken into account when examining derailment rates, each factor is regarded as an indicator of exposure in the context of this research. More precisely, a railway network's traffic density has a significant influence on both railway safety and risk analysis, which can cause derailment rates to fluctuate. Conversely, an increased number of turnouts installed within a network will subsequently elevate the amount of derailments that can be expected to occur on turnouts.

It is important to note that derailment frequencies have a correlation with certain measures of railway traffic exposure, such as car-miles, train-miles, gross ton-miles, or railway tonnes (Dindar et al., 2018a). As previously explained in Section 2.2, the assumption is made that MGT, carloads, and train-miles all have an association with incidents involving derailed goods trains for the purposes of this research.

Table 7.2: Normalised Exposure of RTs to Derailments in the Selected Region.

	Illinois	Kansas	Nebraska	North Dakota	Oregon	Texas
TND	57	25	16	2	2	78
AATV	503.1	344.6	511.1	128.1	54.4	373.4
TRMS	6,986	4,855	3,375	3,330	2,396	10,469
NED	3,514,657	1,673,033	1,724,963	426,573	130,342	3,909,125

In Table 7.2, a variety of different statistical trends and risk indicators are shown, such as the normalised exposure to derailment (NED). The process of obtaining this kind of normalised exposure could involve the presentation of the average annual traffic volumes (in millions of tons) (AATV) of each of the states as an initial indication of derailment frequency. Conversely, the average RT counts in specific states are estimated in line with the TRMS values (Total Rail Miles by State). In other words, there could be a relationship between the turnout counts and the total length of the railway network within the state. The investigation of NED has been conducted based on the product of two indicators, namely AATV and TRMS. The total number of derailments (TND) is also considered to be a feasible response to the resulting output obtained from this product.

It is worthy of note that different circumstantial factors, such as climate patterns, velocity, type of vehicle, maintenance standards and time period all have certain impacts on derailments associated with turnouts. Nevertheless, the selected area offers a beneficial and comprehensible means of diminishing the impacts of such indicators. First, the same climate patterns can be observed across the region, and second, it could be regarded as sufficiently large to reveal a homogenous spread of vehicle class across the specific five-year timespan. It should be considered that derailment incidents resulting from excessive speed are categorised separately according to the FRA reporting, and the specific focus of this research is on the failure of turnout constituents, which is one of the primary reasons for derailments that occur at turnouts.

7.2.4 Assumption on indicators

The traffic pattern implemented in the model, which will be determined in a subsequent section, could be conveyed either in terms of a standard approach for the measurement of traffic across a stretch of rail utilised in railway operations (MGT) or alternatively the volume of wagons that are traversing, namely carloads. More precisely, the latter refers to the aggregate total of the static load across a portion of engaged track, whereas the former refers to the volume of train vehicles traversing a specified portion of rail track with no consideration given to the weight being shipped.

Due to the fact that indictors for railway traffic units and turnout counts are examined to understand their effects on derailment frequencies, it is essential that the assumptions detailed below are made:

- A-1: As will be demonstrated in Section 2.3, the calculation of the MGT traffic values attributed by every state to the considered area (See Fig. 7.1) is made on the basis of the assumption that the MGT traffic values are distributed homogenously across the states.

- A-2: The calculation of the rail-ton miles attributed by every state to the specified area (See Fig. 7.1) is made based on the assumption that rail-ton miles are distributed homogenously across the states.

- A-3: the procedure determined by A-1 and A-2 is applied; nevertheless, carload values are investigated as traffic indicators instead and the assumption is made that they are distributed homogenously across the states.

Conversely, the volume of turnouts, which represents an additional indictor of exposure, utilises:

- A-4: a flowchart, illustrated in Figure 7.2, is implemented for the process of distributing the volume of turnouts throughout the selected region. The assumption is made that the railway network length is correlated to the turnout count.

Data used in the calculations made for A1-A3 is gathered from the Association of American Railroads (AAR, 2016). This particular resource is only utilised in relation to the aforementioned assumptions. Initially, one might expect that these assumptions would not be useful for yielding derailment rates. Nonetheless, an objective of this research is to identify the specific indicator that produces more effective rates under specific conditions.

7.2.5 Area Calculation for the Regions

Seven different US climate zones have been established and detailed in Section 2.1. In line with the distinct climate areas shown in Figure 7.1, layers with different colours are utilised for predicting the anticipated relationship between natural events and the failure of railway components. To achieve this, a novel mathematical model will be necessary for establishing the stochastic model (see Eq. 7.2 and Eq. 7.3).

This sub-section will examine the specific areas of the states determined in Section 2.1 that are included in the selected region. Initially, image processing is performed via MATLAB software (see Appendix D). While the popularity of image processing techniques has increased in the field of railway engineering, it has largely only been applied to remote sensing (Dindar et al., 2017b). Hence, it could be claimed that a different approach is employed in this thesis as it will be used in the consideration of regional exposure to derailment risks.

The overall framework for segmenting and quantifying the states is shown in Figure 7.3. The initial stage within this framework involves the input image, and then each of the climate zones is projected onto the states, as demonstrated in Figure 7.1. The input image incorporates black lines utilised to differentiate each of the zones, states and certain counties. These black lines are subsequently erased and painted in an equal manner using the two adjacent colours. Next, a series of masking methods is applied via the MATLAB toolbox, as shown in Figure 7.4.

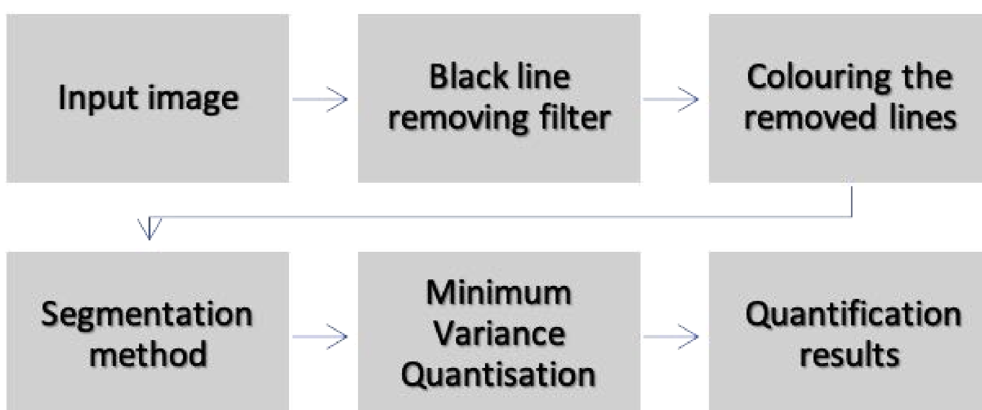


Figure 7.3: Flowchart of the framework for the quantification of the climate zones.

[3]A MATLAB function used in the conversion of an RGB image into an indexed image X utilising minim variance quantisation and dithering.

In the fifth phase, defined as Rgb2ind [3], the maximum amount of colours is determined in the output image's colourmap to conduct a minimum variance quantisation. The numbers are chosen to establish the amount of boxes into which the RGB colour cube (R, G, B) indexed image (comprised of a total of 255 colours) is divided. Resultantly, it is possible to reach the regions of all climate zones as well as the test states, and the subsequent results are shown in Table 7.3.

Table 7.3: Quantification results for the climate zones

Climate zones	Colour	Decimal Code (R, G, B)[a,b]	Pixel Count	Proportion of sizes
1	Pink	(255, 105, 182)	500	0.001
2	Red	(255, 0, 0)	27,575	0.051
3	Brown	(210, 105, 33)	116,157	0.214
4	Yellow	(255,255,0)	48,369	0.089
5	Green	(0,245,0)	169,511	0.312
6	Blue	(0,155,205)	144,744	0.266
7	Purple	(0, 155, 240)	37,505	0.069

[a] The RGB values shown in the column are taken from the image, implying that a value could only be addressed with the equivalent colour in the suggested map.
[b] Coding of RGB values is made within an interval of ± five.

Utilising an Intel ® Core™ i7 -6700 HQ processor, the process of executing 2,000,000 pixels contained in the image via MATLAB lasted around 35 minutes.

7.2.6 Identification of Risk Exposure Indication Combinations

In order to better understand the effect of the new mathematical modelling on the risk exposure by railway transport to derailment, this study is designed to assess the performance of various assumptions against real data. Therefore, combinations of assumptions (traffic units and turnout counts) are required in

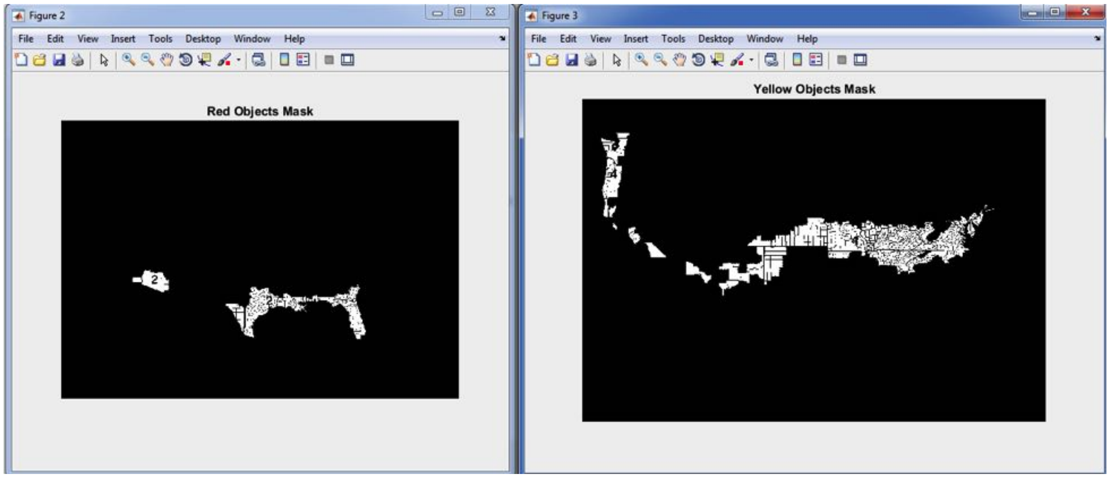


Figure 7.4: Area Segmentation Samples for Climate Regions through Matlab.

order to perform the investigation. Figure 7.5 illustrates the entire structure to which the research has been applied. Dotted lines in the structure are used to express that only one box in the branch is utilised as an information source, whereas straight lines stress that mathematical equations, using all the data in the branch, are required to continue upward.

To clarify the Figure 7.5 in detail, the traffic indicator is selected among four data sources, namely, A-1 to 3, and RQDtd[4] , while either A-4 or RQDtc[5] is used as an additional data source. Throughout Eq. 7.2 (see Section 7.2.7), the exposures of segmented regions are calculated with the chosen data source. Derailment estimates, then, are calculated using the exposures and real derailment counts by means of Eq. 7.5 (see Section 7.2.7). Therefore, the selections of two different kinds of indicators within the two sets in which order is regraded are matched. Eight combinations of two indicators can be drawn from these two indicator sets: RQDtd and RQDtc (R1), RQDtd and A-4 (X1), A-1 and RQDtc (X2), A-1 and A-4 (X3), A-2 and RQDtc (X4), A-2 and A-4 (X5), A-3 and RQDtc (X6), and

[4]Real quantitative data for railway traffic density.
[5]Real quantitative data for turnout count.

A-3 and A-4 (X7).

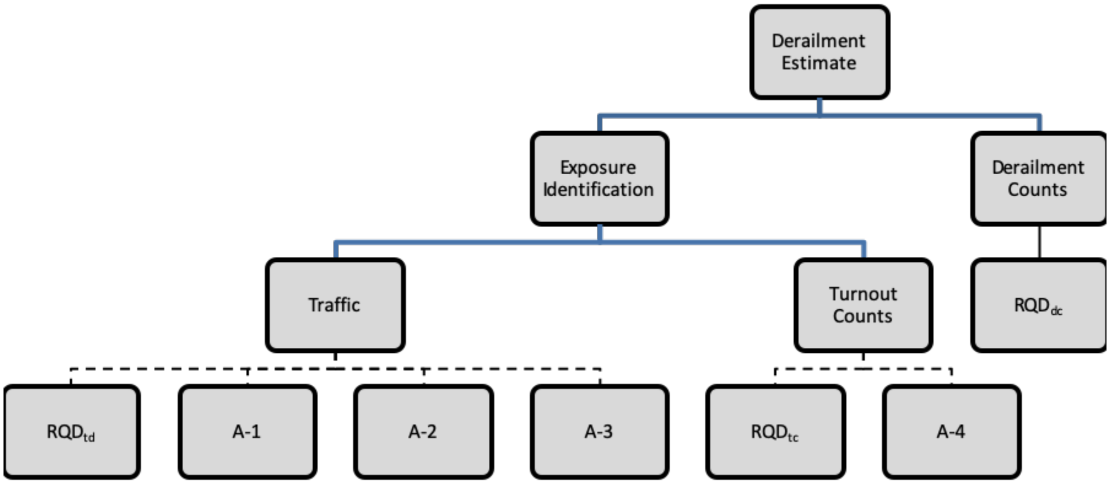


Figure 7.5: Structure for the use of the assumptions and real database.

7.2.7 Comparable Model Development

To conduct an analysis on the component failure rates at RTs and understand the precision of the mathematical assumptions on risk exposures, it is necessary to appoint a novel stochastic model, which is capable of estimating the rates of the derailment accidents within the chosen zone as effectively as possible. The novel model is required to respond both to real exposure values (the number of turnouts and traffic volume) and the values created by a set of assumptions using inexact data.

The structure of the model, therefore, is composed of a fixed formula, which is capable of addressing various kinds of exposure. Hierarchical modelling has been suggested to precisely estimate derailment rates of component failures at RTs in a given region (Chapter 7). The modification of the suggested model Albert (1988) is illustrated in Eq. 7.1.

$$p(\alpha, \mu| \text{ data }) = \kappa \frac{z}{\Gamma^6(\propto)(\alpha+z)^2\mu} \sum_{i=1}^{18} \left(\frac{\propto^\alpha \ \mu^{-\alpha}\Gamma(\alpha+\lambda)}{(\propto /\mu + \pi)^{(\alpha+\lambda)}} \right) \tag{7.1}$$

where α and μ are hyperparameters of a gamma function, κ is a proportionality constant, and i indicates state i within the chosen region. The verification of the model had been achieved (Albert, 1999). Thus, it can be identified that the marginal posterior density of (α, μ) is discovered through the suggested equation. Also, as the chosen region is made up of proportions from 18 different states i= 1, . . . , 18. That is, each state contributes unequally to the marginal probabilities. Further, an MCMC algorithm is used to find a kernel density estimate of the simulated draws from the marginal posterior distribution (Albert, 1996).

In addition, π in Eq.1 is found by

$$\pi_i = \mathbf{e}_i \cdot \lambda_i \tag{7.2}$$

where λ denotes the occurrence rate in a given state (A-1, A-2 or A-3) , and e (A-4) is the exposure (per year). The mathematical formula for the exposure is shown below.

$$\mathbf{e}_i = \sum_{i}^{18} w_i.TRMS_i.\text{AATV}_i, \quad i = 1, \ldots, 18, \quad \forall i \in \mathbb{N} \tag{7.3}$$

where w_i is the proportion of the area corresponding to ith state in the assigned climate, $i = 1, \ldots, 18$. For instance, if a quarter of the area that a state possesses falls into the chosen region, then w_i is 0.25 .

$$\lambda_i = \sum_{i}^{18} w_i \cdot \lambda_i, \quad i = 1, \ldots, 18, \forall i \in \mathbb{N} \tag{7.4}$$

where λ_i represents occurrence rate for the proportion of ith state situated on the region. The acquisition of the occurrence rate (λ) corresponding to the chosen region follows a process equivalent to that used for the acquisition of the exposure (e). That is, after determining a constant value of w_i for ith state, the values of e and λ associated with this state are found by using Eq.7.3 and Eq.7.4. In addition, Eq.7.3 and Eq.7.4 are used for the assumptions (see Section 4.1).$Eq - 1$ through Eq.7.5 consist of the second level of the hierarchical model. The first level is then simplified in the following equation in order to obtain derailment rates which are sampling from a gamma $(\alpha, \alpha/\mu)$ distribution of the form.

$$g_1(\lambda | \propto_1, \mu) = \frac{1}{\propto_1 \Gamma(\alpha_1)} \left(\frac{\propto_1}{\mu}\right)^{\alpha_1} \exp(-\alpha_1 \lambda/\mu), \quad \lambda \in [0, +\infty) \tag{7.5}$$

where α_1 is the parameter of an inverse gamma function with hyperparameter (Albert, 1999). On the other hand, the state with the smallest estimated derailment rate for each combination can be identified through the following formula:

$$E\left(\frac{\text{derailment count } + \alpha_1}{\pi + \left(\frac{\alpha_1}{\mu}\right)}\right) \tag{7.6}$$

7.3 Results

To both understand the performance of the assumptions compared to the real database and analyse the impacts of the assumptions on the estimation of turnout component failures, the proportion of each state within the region is firstly computed. Table 7.4 has been established by the methodology presented in Section 7.2.6. It exhibits the complete details of the observed data and prediction. The mathematical modelling has then been expanded to include the other two units of railway traffic, namely, rail ton-miles and carloads. As observed, some prediction models underperform compared to the RQD. Some relatively small proportions of states in the region, such as the proportions from AR and NY, have assumptions which diverge from RQD, while the remaining states' assumptions, (e.g. DC, DE, and NJ), are observed to perform well for the most part. Regardless of either how large or small the proportions from the states are or how much railway traffic is present in the states, an assumption which is based on turnout counts seems to fluctuate widely.

Based on the results shown in Table 7.4, any quick decision for estimation of the derailments is not advisable. The maximum likelihood method (MLE), a method determining values for the parameters of a model, is used to reveal the impact of the states on derailment counts on logarithmic x-axis in Figure 7.6. That is, the aim herein is to estimate the turnout-related derailment rates per unit of unique exposure (λ) in which each state has. Thus, the MLEs (y/π)[86] for the chosen states show obvious inconstancies through each combination of exposure indicators. In general, New Jersey, Pennsylvania, and Georgia can be considered not to be at high risk of derailments considering their low turnout

[6]The number of derailments per unit exposure

Table 7.4: Derailment-risk indicators for the states located in the chosen region.

	Railway Traffic				**Turnout Counts**	
	ArcGIS	*Predictions*			*ArcGIS*	*Predictions*
States	RQDtd (MGT)	A-1 (MGT)	A-2 (Rail ton-miles)	A-3 (Carload)	RQDtc	A-4
Arkansas	701	4,341	34	549,527	66	969
The District of Columbia	320	320	32	584,800	319	36
Delaware	438	478	17	310,600	145	450
Georgia	3,730	2,099	24	531,664	117	1,090
Illinois	11,549	18,643	170	4,035,137	1,272	4,237
Indiana	5,356	8,809	91	2,156,692	989	2,321
Kansas	50,510	35,102	2,31 4	120,533	2,914	5,862
Kentucky	20,668	2,0678	252	4,351,700	1,526	4,694
Maryland	5,144	4,743	81	1,879,260	620	1,234
Missouri	35,543	33,979	311	5,944,221	1,703	5,201
North Carolina	5,037	5,713	40	695,750	590	2,812
New Jersey	1,294	1,163	26	883,979	645	1,041

Table 7.4 *(Continued)*.

	Rail Traffic				Turnout Counts	
	ArcGIS	*Predictions*			*ArcGIS*	*Predictions*
States	RQDtd (MGT)	A-1 (MGT)	A-2 (Rail ton-miles)	A-3 (Carload)	RQDtc	A-4
New York	40	339	1	35,286	190	130
Ohio	4,151	6,333	37	848,620	288	1,228
Pennsylvania	1,747	2,016	15	340,029	627	724
Tennessee	17,143	15,856	179	3,242,668	1,243	3,822
Virginia	17,489	17,486	159	2,851,607	1,301	5,786
West Virginia	9,907	5,899	85	1,385,896	464	1,764
Total	190,766	183,996	1,786	34,747,969	14,697	43,401

counts and railway traffics. It is worth noting that changes in the log exposure (x-axis) cannot be compared as the unit of exposure indicators vary throughout the combinations. However, this kind of estimate is open for discussion, as derailment events at turnouts, in particular those caused by component failure, are rare [7]. To remedy such a situation as much as possible, a Bayesian estimate, based on prior knowledge of the derailment rates, is used as shown in Section 7.2.5. As shown in Figure 7.6, the fact that a number of MLEs are placed at a low scale might also be expressed as proof of the necessity of performing a hierarchical Bayesian analysis.

Hyperparameters (α and μ), which are nested on the first floor of the structure (see Eq.5), must be simulated using the marginal posterior distribution. It is noted that the posterior density for $(\log \alpha, \log \mu)$ is not shaped in a desired way. The normal approximation to the posterior, therefore, is insufficient for proper simulation. Metropolis within the Gibbs algorithm[8] allows the log-hyperparameters to be simulated. The initial trials in the simulation for the two conditional distributions for each combination have been assigned the equivalent starting point (-5, -22). The acceptance rates in the simulation are limited to 20%, and the number of iteration in the simulation is 50,000. Figure 7.7 illustrates the simulation trace plots for the assigned values of the hyperparameters (α and μ) from the Bayesian hierarchical model.

Considering the regions, which are expected to have higher derailment rates, Tables 7.6 and 7.7 illustrate the statistical outcomes of the given combinations. X7, which is made up of two assumptions (A-3 and A-4) and X6, which is made up of real data and an assumption (RQD and A-4), yields the worst estimates.

[7] Due to nature of MLE, as the number of derailments (y_i) becomes smaller, the estimate becomes worse. Moreover, if any derailment does not occur in a chosen region, it might still be quite unwise to bet that the estimate in question will never occur in the future.

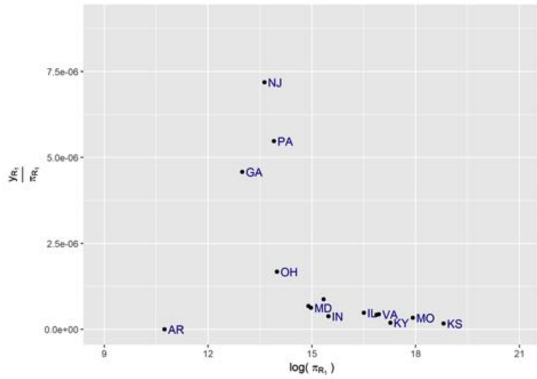
[8] Available at https://www.rdocumentation.org/packages/LearnBayes/versions/2.15.1/topics/gibbs

Derailment rates in Kansas, which has one of the largest railway networks and the heaviest railway traffic in the chosen region, show that the $\hat{p}_1$ and $\hat{p}_{24,25,26}$ values, in particular for X6 and X7 , deviate by 25 percent in comparison with R1.

As seen in the traces for the combinations Q6 and Q7 (fully formed by assumptions) in Figure 7.7, there are wide fluctuations present, likely as derailment exposure indicators show inconsistency through the states.

The more symmetric the simulated draws on the right and left tails of the number of observed derailments are, the better the estimate. For instance, the first three histograms in Figure 7.8 indicate the robustness of the hierarchical model, while the distribution for GA does not. However, the estimate is seen to deviate slightly in regions with low numbers of derailments, which does not affect substantially the number of derailments in population, as the entire region has 107 derailment cases.

Table 7.5, for instance, shows some statistical outcomes of simulated draws for New York railway Network which has a low number of derailments ($\mathrm{Y}_{\mathrm{NY}} = 1$) . Probing μ_{NY} (mean of the draws) and σ_{NY} (standard deviation of the draws), all of the combinations are said to be clustered around 0, which is not desired, as one derailment is reported in the region. Therefore, the actual coverage probability close to the nominal value of (W^-, W^+) is satisfying. However, as this particular derailment case is rarely observed, the point estimate for the actual count of the reported derailments, $\hat{p}_1$, is extended with the probability of zero derailments or two derailments $\hat{p}_{0,1,2}$. As expected, $R1_{NY}$ yields the best outcome with a probability of 0.99998. The other combinations, however, are not poor estimates.



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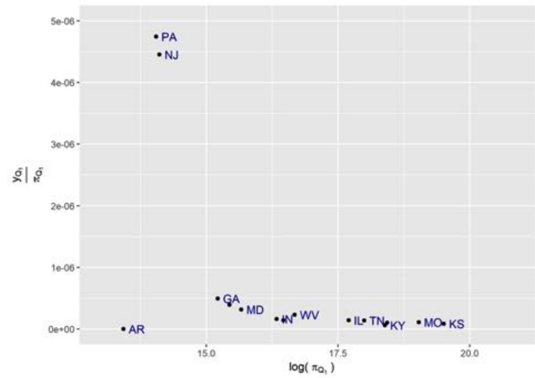

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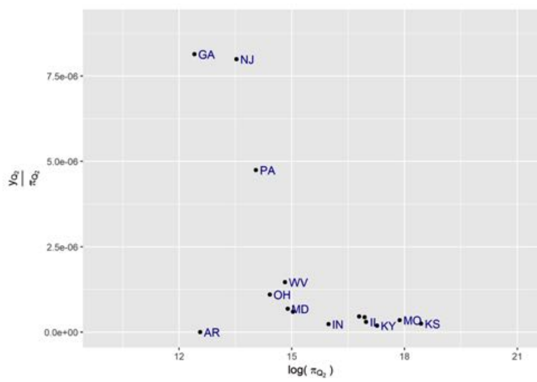

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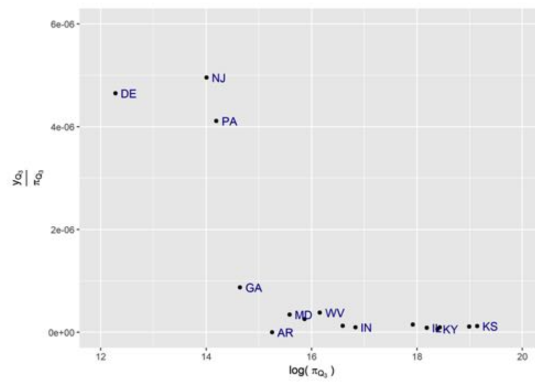

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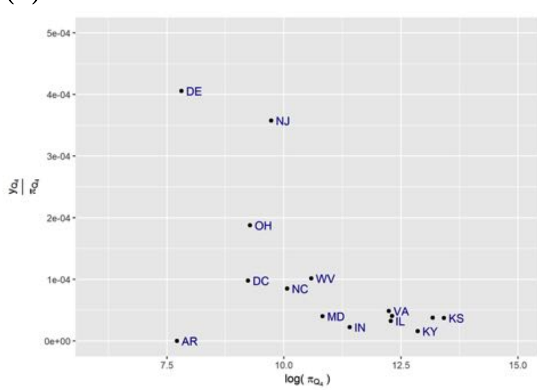

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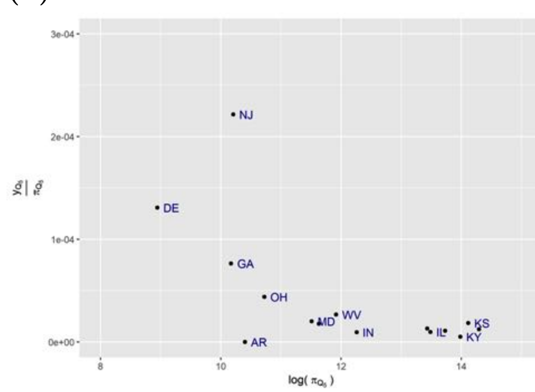

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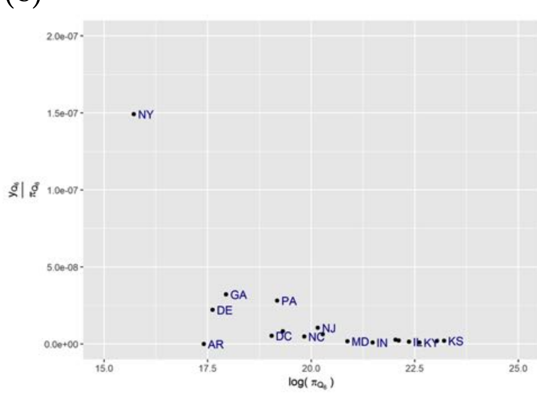

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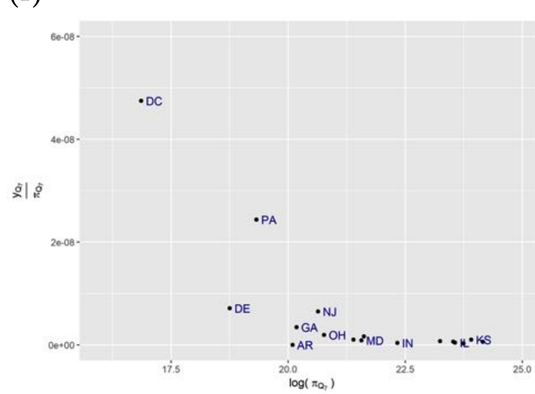

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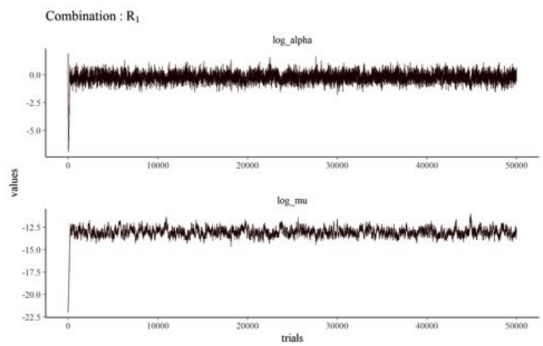
Figure 7.6: MLE Estimates of the chosen states through eight different combinations.



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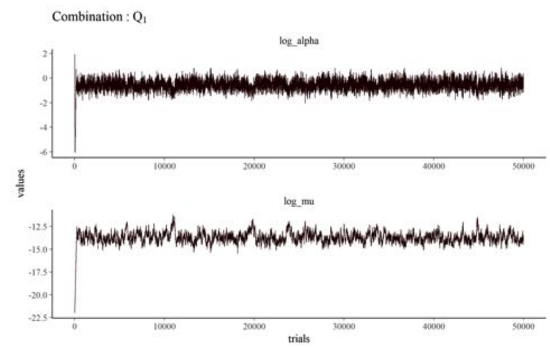

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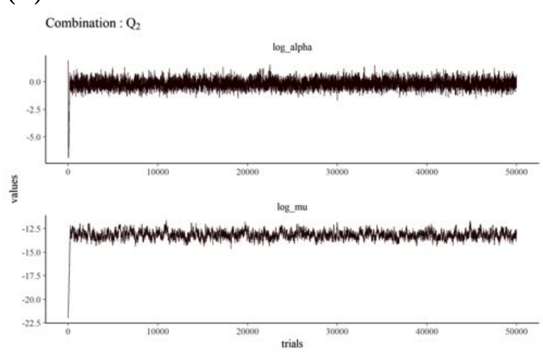

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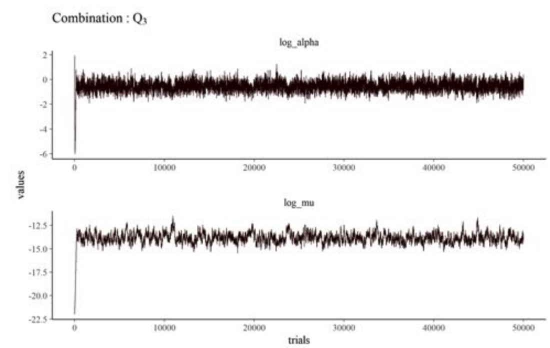

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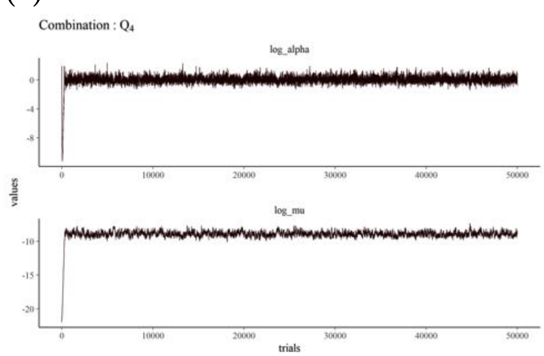

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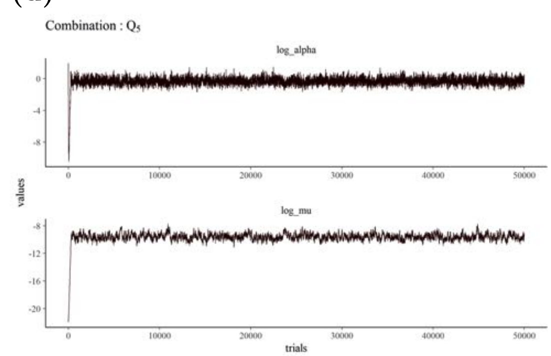

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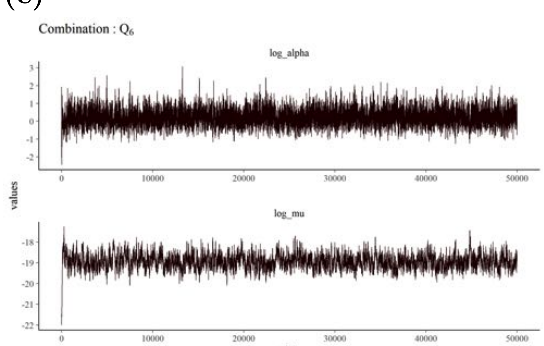

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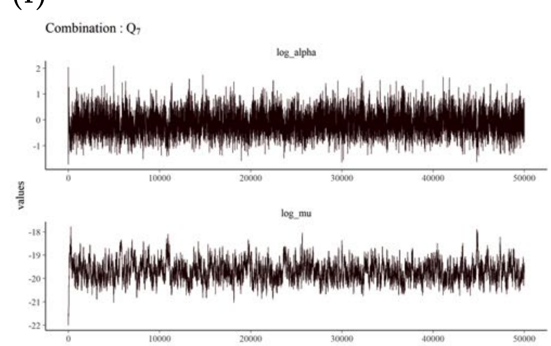

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Figure 7.7: Trace Plots of the MCMC sampling procedure for the combinations of $\log(\alpha)$ and $\log(\mu)$.

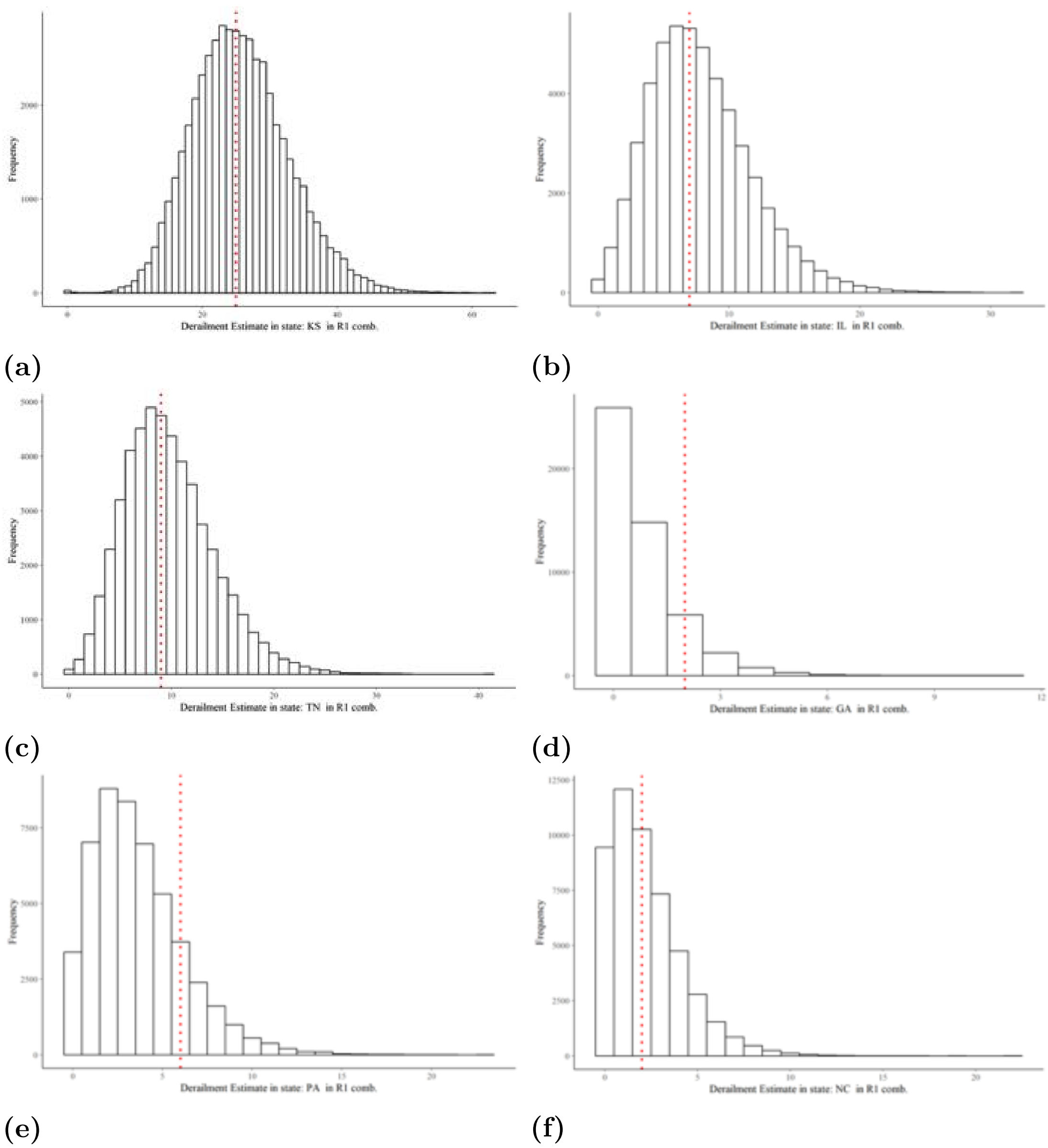

Figure 7.8: The number of observed derailments (red dotted line) and histograms of the simulated draws from the posterior predictive distribution for several states for R1.

Table 7.5: Descriptive statistics for the Bayesian hierarchical model assigned with various exposures for the New York railway network

	Min	Q_1	μ_{NY}	Q_3	*Max*	σ_{NY}	W^-	W^+	$\hat{p}_1$	$\hat{p}_{0,1,2}$
$R1_{NY}$	0	0	0.03432	0	3	0.1902179	0.02994607	0.03300592	0.03144	0.99998
$X1_{NY}$	0	0	0.02144	0	4	0.1517260	0.01859588	0.02103790	0.01978	0.99994
$X2_{NY}$	0	0	0.23800	0	6	0.5387683	0.15607880	0.16249350	0.15926	0.99310
$X3_{NY}$	0	0	0.14550	0	5	0.4181237	0.10394490	0.10935550	0.10662	0.99726
$X4_{NY}$	0	0	0.05120	0	3	0.2308671	0.04502250	0.04872713	0.04684	0.99988
$X5_{NY}$	0	0	0.02758	0	5	0.1710553	0.02421271	0.02698019	0.02556	0.99994
$X6_{NY}$	0	0	0.07128	0	3	0.2727648	0.06186831	0.06615868	0.06398	0.99997
$X7_{NY}$	0	0	0.03484	0	3	0.1908583	0.03070778	0.03380409	0.03222	0.99994

9

Min and Max: the minimum and maximum intensity values at the histogram, respectively.

Q1 and Q3: the values that cut off the first 25% and 75%, respectively, of the data when it is sorted in ascending order.

σ_i: standard deviation of derailment probability values for given i^{th} state.

W^- *and* W^+: a confidence interval for a proportion in a statistical population of derailment probability values.

$\hat{p}_i$: the proportion of the point estimate for the actual count of the reported derailments to the whole.

$\hat{p}_{i-1}, i_{i+1}$: the proportion of the point estimate for the actual observation along with the two nearest estimations to the whole.

Table 7.6: Descriptive statistics for the Bayesian hierarchical model assigned with various exposures for the Illinois railway network

	Min	Q_1	μ_{IL}	Q_3	Max	σ_{IL}	W^-	W^+	$\hat{p}_1$	$\hat{p}_{0,1,2}$	
$R1_{IL}$	0	5	7.592	10	32	0.1902179	3.919311	0.1012163	0.1065646	0.10386	0.30908
$X1_{IL}$	0	5	7.511	10	30	0.1517260	3.86311	0.1021653	0.1075354	0.10482	0.32068
$X2_{IL}$	0	5	7.705	10	34	3.907449	0.1046964	0.1101239	0.10738	0.32260	
$X3_{IL}$	0	5	7.517	10	33	0.4181237	3.852057	0.1043998	0.1098206	0.10708	0.32424
$X4_{IL}$	0	5	7.792	10	32	3.919311	0.1035692	0.1089713	0.10624	0.31970	
$X5_{IL}$	0	5	7.604	10	39	3.894708	0.1027783	0.1081624	0.10544	0.32190	
$X6_{IL}$	0	5	7.972	10	32	0.2727648	3.940043	0.1017303	0.1070905	0.10438	0.31486
$X7_{IL}$	0	5	7.741	10	35	3.920828	0.1043800	0.1098004	0.10706	0.32066	

Table 7.7: Descriptive statistics for the Bayesian hierarchical model assigned with various exposures to the Kansas railway network

	Min	Q_1	μ_{KS}	Q_3	Max	σ_{KS}	W^-	W^+	$\hat{p}_1$	$\hat{p}_{0,1,2}$
$R1_{KS}$	0	21	25.84	30	74	7.176168	0.05486403	0.05892406	0.05686	0.16744
$X1_{KS}$	0	21	25.55	30	62	7.121259	0.05164026	0.05558833	0.05358	0.16118
$X2_{KS}$	0	21	25.73	30	70	7.164428	0.05486403	0.05892406	0.05686	0.16672
$X3_{KS}$	0	21	25.48	30	62	7.130782	0.05631929	0.06042857	0.05834	0.16706
$X4_{KS}$	0	21	25.71	30	63	7.146079	0.05382199	0.05784626	0.05580	0.16664
$X5_{KS}$	0	21	25.49	30	67	7.146889	0.05311430	0.05711406	0.05508	0.16970
$X6_{KS}$	0	21	25.8	30	62	7.163830	0.04832036	0.05214875	0.05020	0.149146
$X7_{KS}$	0	21	25.5	30	63	7.089469	0.04512061	0.04882900	0.04694	0.13756

7.4 Discussion

The quantification of risk on the basis of a Bayesian hierarchical model is an innovative method for performing safety analysis in the context of railway engineering and offers significant prospects for implementation in a variety of different areas of railway engineering fields. It is contended in this thesis that the mathematical assumptions utilised as indictors of risk have certain distinctions and along with recorded observations, they are employed for analysing derailment risk with a specific focus on constituent breakdowns at RTs. The findings will improve the accuracy of estimating derailments, thus concretising the process of managing railway risks. Accordingly, it is possible to reduce any potential serious outcomes by enhancing the comprehension of specific factors that influence incidents of derailment related to this type of failure. Hence, this Chapter satisfies the need for the assessment of the effectiveness and practicality of assumptions, representing one of the factors that have an influence. The suggested methodology utilises a dataset formed of real values (acquired with ArcGIS) as well as a single assumption (comprising a mathematical technique) for the derailment count. In order to remove the impact of weather patterns on the number of derailments, a sufficiently large region is established on the basis of published climate reports. A total of 18 states are incorporated into the region to be examined, each of which exhibits distinct exposure levels. The states' risk indicators, or risk exposures, are calculated during this process by utilising either an actual FRA database, databases that have been produced mathematically, or a mixture of the two. Subsequently, the three states considered to have the least to most level of risk are chosen to benchmark the results. On the basis of a proven Bayesian hierarchical model, a comparison is made between the positive and negative aspects of using actual data and assumptions or a combination of the two, as explained below:

- In terms of the regions where the risk indicators are relatively low, such as New York state, the derailment estimations yielded from the assumptions were similar to the real observations. Nevertheless, it appears that all estimates are not capable of calculating estimates for lower amounts of derailments and are therefore determined to be the estimates with the highest sensitivity in those areas. The main cause of the unreliability of estimations from each of the combinations could be the scarcity of data in the risk indicators and the reduced number of derailments. In order to resolve this problem, one suggestion is to extend the period of time chosen for the derailment analysis. For the purposes of the present study, the time period selected for analysis of derailment incidents was the previous 5 years. A greater number of derailments would enhance the accuracy of the results. This means that sampling should generate a subset that is representative of all the data. To meet the sampling analysis criteria, a total of 50,000 derailment samples were produced, which appears to be sufficient to establish a conclusion by taking into account the even distribution of bars illustrated in Figure 7.8. Conversely, due to the fact that smaller areas do not significantly affect the estimation of the overall amount of derailments for the whole region, the aggregate number of derailments could be acquired in the intended manner.

- In terms of the areas where the indicators have moderate levels of risk, such as Illinois[10] , it is ascertained that one can precisely estimate the derailment

[10]In fact, Illinois does have relatively high risk indictors. Nevertheless, the territory within Illinois that is included in the selected region is determined to represent a risk of derailment that is lower in comparison to the whole state.

frequencies under all conditions of ambiguity, which could be generated by the assumptions. It is important to note that this study is performed based on a hierarchical Bayesian model to estimate the parameters of the posterior distribution of derailments associated with turnouts in two phases. Through the application of this cutting-edge method, it is possible to gather further evidence with respect to the previous distribution. The approach facilitates an innovative prediction of the actual derailment frequencies as allowed by the limits of the input data. It can be seen that all regions whose risk indicators are low, such as the turnout counts and the density of goods traffic, can be examined using one of the proposed assumptions A1 to A4 (see Section 7.2.2).

- In terms of the areas where the indicators have high levels of risk, such as Kansas, it is found that certain assumptions, specifically those that are dependent on turnout numbers, exhibit deviation from the observations. As opposed to the first bullet point where a larger-sized sample was desired, such sample sizes in the assumptions in this scenario normally reduce the levels of accuracy of derailment estimations. This means that the reduction in accuracy for sample sizes with greater magnitude is predominantly connected to negligible or even a complete lack of data. This could largely materialise as a result of flaws within the assumptions or a significant reliance on the actual data. Additionally, it could be caused by the improved statistical findings due to a heavy-tailed (asymmetrical) distributions in these cases.

- In terms of the assumption types, it can be determined that the assumptions in relation to turnout numbers represent a potential deficiency even in cases where they are produced mathematically based on a definite belief. This study utilises the proportion of turnout numbers and the length of the railway networks. As the population densities of European countries are comparatively higher than those within the United States, the railway networks in Europe need increased numbers of turnouts in shorter railway sections. In the event that reliable information on estimating the turnout count within a specific region is not readily available, particularly those characterised by high levels of exposure, an subjective assessment provided by a specialist or an expert could be used prior to performing the analysis. This indicates that the study considers that this US region has one turnout every 1.18 miles, even though this implies that there is a significantly higher turnout count than is in fact the case within the United States. In other words, every state has distinctive properties, which have an impact on the nature of the railway networks that they construct. Thus, specific turnout counts for these regions are required, determined by utilising actual data or expert opinions, in order to achieve the proper sampling.

7.5 Conclusion

Chapter 7 has directly been influenced by Chapter 2, Chapter 3, Chapter 4 and Chapter 6. As identified in Chapter 2, the same methodology based on the stochastic Bayesian hierarchical model of Chapter 6 is used. The investigation is established on turnout component failures, which were determined as the most derailment-causing factor in Chapter 3. The proposal of Chapter 4 on regional segmentation is applied to the overall methodology of Chapter 7. In order to benchmark the performance of the stochastic Bayesian-based risk management over deterministic approaches, this chapter offers a study. It is found that the proposed novel risk management framework through stochastic process yields remarkably better results. Therefore, Chapter 7 validates the usability of the proposed model to the railway industry.

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CHAPTER 8

CONCLUSION

8.1 Introduction

Motivated by insufficiencies and questions arising from the extanded literature, the overall objective of this thesis is to understand and expand on the knowledge surrounding the causes of derailment that prevent the smooth function of railway operations. Through the novel methodologies based on the application of both quantitative and qualitative techniques, a series of case studies has been presented for the purposes of applying Bayesian analysis to the field of railway incident analysis.

This chapter summarises a large number of significant findings pertinent to the research questions and offers overall conclusions on the basis of the results of the abovementioned studies. Moreover, an assessment is conducted in regard to the strengths and weakness of the thesis as well as proposals for additional research into the areas of railway transportation and the analysis of railway accidents. The chapter is concluded with suggestions for three specific groups of stakeholders operating in the transportation engineering domain: accident investigators, risk analysts and railway researchers.

8.2 Summary and Contribution of Research Findings and Implications

8.2.1 Identification of appropriate risk analysis techniques for railway turnout systems

The first thesis objective was related to the determination of the risk analysis technique that produces the best results. As this area has received no attention in the extant literature, it was necessary to conduct such a study in order to resolve the deficiency identified by the literature review. The study offers a novel integrated strategy in regard to how the numerous risks emerging from a variety of origins in railway turnout systems can be addressed through the appropriate identification of multi-disciplinary risk analysis techniques for systems with high complexity. To achieve this, accessible open researches are critically examined on the basis of comparisons, sector experiences and assumptions. As a result, several risk analysis techniques based on qualitative and quantitative approaches are advanced to further the understanding of technical factors, such as aging, deterioration, and defective signalling in railway turnout systems.

This critical literature review has examined the prevailing methods and applications related to the analysis and modelling of risk, and has uncovered significant knowledge deficiencies in the sector. It has been observed that the sector utilises a broad scope of risk analysis approaches and produces different results, thus leading to diverse and inconclusive maintenance strategies. Studies have demonstrated that the railway sector must particularly focus on monitoring and managing related risks so as to enhance public safety and operational reliability. Hence, this thesis introduces cutting-edge methods of risk management based on a systems thinking strategy, the diversified nature of developing risks and the various different risk analysis techniques. These methodologies have been comparatively evaluated via a through discussion related to railway accidents. A summary of practical recommendations has been provided for railway operators for the purposes of enhancing the field of railway transportation with particular focus on railway turnouts.

It is undeniable that the analysis, modelling and management of risk in relation to railway networks offers indispensable benefits to railway operators and bodies in terms of prediction a variety of situations and subsequently reducing their impacts. Referring to specific points emerging from the discussions, the factors detailed below are deemed to be worthy of further investigation:

- The advantages of the enhanced ability to choose, assess and consider pertinent factors involved in risk analysis modelling in order to satisfy appropriate safety standards for railway turnout systems; for example, this could include a continually updated procedure in which a significant volume of outputs is acquired in each specific instance through the use of numerous different techniques and inputs, and then making a comparison between the outputs and the real data on an annual basis for optimising and calibrating expectations.

- The reaction of more integrated conditions for distinct types of risk analysis; the differing degrees of certain risk factors, like the age of railway parts and environmental considerations, can be combined to generate a more accurate prediction of the probability of occurrences at turnout systems, thus indicating the quantitative relationship that exists between the two, In this case, integrating the two factors could enhance the comprehension of the actual risk levels instead of smoothing out the general risks.

- The consequences of constructing a data pool with improved effectiveness, where any newly discovered incidents are anticipated to happen and data are insufficient. As frequently observed subsequent to processes of technology transfer, it could be more advantageous to include the outside data into the extant models with a suitable model to generate UK-suitable estimations for frequencies and outcomes.

- The impact of the same in-depth Mapping Top Events for estimates across the sector; in other words, a hazard on one side can sometimes by separated into multiple categories on the other. It could be useful to standardise titles and subtitles for the determination of precise levels of risk in specific cases.

- A variety of quantitative cost-benefit optimisations for all items listed above to ascertain what should be developed further.

To summarise, the proposed risk analysis technique selected is the Bayesian method. A variety of different unidentified factors (such as the effects of climate) are potential underlying causes of derailments. Due to the fact that only a limited number of researchers have attempted to conduct analysis on derailments with a more limited focus, and a significant deficiency exists in the associated literature, it is necessary for the thesiss to develop novel methodological approaches based on Bayesian analysis, with specific reference to Novel Causal Bayesian Networks.

There are various benefits to constructing a Bayesian network on the basis of causal instead of association information. Firstly, the judgements necessary when constructing the model have greater meaning, have increased accessibility and therefore have enhanced reliability. Readers of this thesis could enhance their appreciation of this aspect by endeavouring to build a DAG presentation similar to that found in the second study. This type of exercise not only demonstrates that certain independencies can be accessed more visibly by the mind than others, but additionally that conditional independence judgments are accessible, and thus are reliable , only when they are anchored onto more fundamental buildings blocks of our knowledge, such as causal relationship.

An additional benefit of constructing a Bayesian network on causal associations, which is crucial for comprehending causal organisations, is the capability to reflect and react to outside or sudden variations. Where the system within the environment is locally reconfigured, it is possible to translate it, with only small changes, into an isomorphic rearrangement of the topology of the network.

8.2.2 Assessment of turnout-related derailments by various causes

The previous study has been performed to assess the feasibility of the risk analysis techniques in relation to the particular topic covered by this thesis. The process of analysing risk generally commences with identifying the risks and different contributory factors. The study established risk groups and assigned them priorities in order to rank them in order of most to least critical importance. As a result, the study findings facilitate the understanding of the risk analysis/-management of railway turnout systems whereby their immediate, causal and contributory factors should be able to manage or mitigate the actualisation of strong likelihood/high consequence of risk incidents.

Incidents of derailed trains on turnouts are found to be responsible for most accidents that happen on heavy train lines. Even though the traffic density on metro systems (underground) is the same as on heavy lines, the average number of derailment incidents is significantly less. Light rail, characterised as urban systems of transportation functioning at ground level, has also been demonstrated to account for numerous derailments connected to turnouts and is therefore highly susceptible to this kind of incident.

It is demonstrated that the placement of the turnout, such as in a yard or siding, is investigated to ascertain its level of correlation with derailment frequency. Train vehicles on main line tracks have greater vulnerability in comparison to those in yards, sidings or industrial tracks. Furthermore, if the speed allowed when traversing turnouts is increased, the frequency of resulting incidents rises accordingly. Nevertheless, there is a complex association between velocity and derailment, which necessitates additional investigation. It has been found that certain causes of accidents have strong correlations, while this is not the case for others.

The primary statistical data on incidents of derailment at turnouts is demonstrated by data based on official reporting by the Rail Accident Investigation Branch. The main reasons for derailment are railway infrastructure, operational and human elements, respectively. Moreover, the amount of infrastructure connect with the failure of various turnout components is the greatest, while the turnout components that fails most frequently is determined to be the switch. The second most frequent category of failure is related to stretchers. Apart from component breakdowns, both operational and human aspects appear to be important contributory factors to the prevalence of derailments.

The causal factor with the greatest importance is component failures, representing one quarter of the overall total. Additional factors include those related to the environment and human aspects. It appears that turnouts have strong susceptibility to extreme hot/cold conditions, which lead to a variety of geometry issues, as well as driver errors such as communication deficiencies. The study has also addressed contributory factors, where the most common is maintenance, which is caused by the lack of regularly scheduled work. Hence, derailment specialists within the UK have recommended that the frequency of maintenance be increased. However, it is believed that climate also has potentially significant effects on the failure of turnout components.

8.2.3 Bayesian Network-based probability analysis of train derailments caused by various extreme weather patterns on railway turnouts

In the context of engineering operations, it has been determined that BN is an effective instrument for the representation of ambiguous knowledge. Additionally, the prior study has facilitated the understanding of the different reasons behind derailments. This research has uncovered the extent to which climate trends influence derailments at railway turnout systems and the types of causal factors. It is suggested that Buckley's probability calculation be utilised based on confidence intervals to acquire conditional and marginal probabilities, as well as to obtain prior and posterior conditional probabilities in the proposed climate-related derailment Bayesian Network (WRDBN). Even though data have been acquired by investigating approximately 18,000 reports on US incidents, it is evident that this type of derailment is not a common occurrence. As opposed to more traditional approaches, the aforementioned confidence interval method is believed to enable flexible decision making in regard the likelihood failure causing derailments. This means that it allows probabilities to be obtained in WRDBN in the form of intervals rather than crisp values. Probability intervals utilising data are determined via a theoretical foundation of probability and confidence intervals.

It has been concluded that seven primary causes exist, namely R1 to R7 (Severe Wind, Snowfall, Fog, Precipitation, Flooding, High Temperatures, Low Temperatures), as well as seven intermediate nodes, namely I1 to I7 (Aerodynamic issues, Blockages, Slipping, Vision impairment, Track bed issues, Geometry issues, Component failures), which are influenced by climatic conditions and cause derailments on turnouts. Several of these nodes, like freezing precipitation, liquid precipitation and extreme winds, are of particular interest. The confidence probability intervals associated with these nodes are seen to be greater in comparison to the others, due to the fact that the impact of modifying the prior/posterior likelihood of the leaf node (derailment) is significantly elevated. To summarise, this thesis advances an alpha cut-based FBN model on the premise that it is applied in an organised, methodical and rational way that facilitates the provision of risk assessment outcomes for railway turnouts.

To conclude, this unrivalled study uncovers the causal associations between the main causal factors and subsystem breakdowns, thus causing derailment, due to several climate events. Additionally, the model, which is specifically focused on non-frequent incidents, has been advanced for the purposes of identifying the likelihood and fundamental causes of derailments. Consequently, it is anticipated that certain climate-associated causes of derailments at railway turnouts, which have the potential to damage train vehicles, railway equipment and cause service disruption as well as injuries and even facilities. The study is determined to facilitate a smooth railway operation. The valuable understanding into the impact of climate on derailments will be beneficial for the sector in terms of managing railway operations in conditions of weather uncertinities.

8.2.4 Bayesian based- Human Error Probability Assessment of Derailments at Different Kinds of Turnouts

Consistently functioning railway operations necessitate dedicated engineering systems, where every employee has the same level of importance as the mechanical components that form the system. As the scope and coverage of the systems expand, the influence of human factors on the design of railways increase in a manner that leads to optimised performance. Hence, comprehensive examination of the causal nature of human mistakes in railway derailment incidents is essential for enhancing the safety margins and reducing the frequency of derailments. A model that probabilistically predicts human mistakes utilising a Bayesian Network (BN) is proposed for augmenting the safety margins in the context of the railway sector. The BN incorporates the modelling of ambiguous human mistakes facilitated by a distinct Fuzzy algorithm that translates the linguistic (provided by railway workers) into mathematical expressions.

In order to discern possible errors, individual interviews were conducted with railway employees. Both descriptive and informative data were gathered from a total of 10 professionals, with a particular focus on a specific phenomenon (derailed trains on turnouts). The gathered data has facilitated the development of a probabilistic model that is representative of conditional reliance, and hence causation. The data additionally assisted in preparing the questionnaire, which was administered to more than 50 railway workers. The linguistic values provided by these employees were then translated into mathematical expressions by applying a novel approach utilising fuzzy memberships.

The human errors related to the utilisation of switches are determined to be responsible for one quarter of all incidents that result in derailments at turnouts.

The primary causes of this specific issue are the implementation of obsolete turnouts, which are not equipped with any form of turnout motor that can be used in the electrical and remote operation of the railway switch. It is found out that manual turnouts are still in operation on the railway network in Turkey. Specifically, the entrances and exits to sidings located in rural areas still present significant risks. However, physical factors impacting employees, such as excessive tiredness causing sleep, employee work or motion impairment, debilitation as a result of injuries or sickness and impaired efficiency or perception due to the consumption of alcohol or drugs are recognised as having powerful conditional reliance on the connected nodes, specifically the utilisation of switches, control mechanisms, locomotive handling and velocity. Nevertheless, as the values for both train handling and velocity are not sufficiently high for consideration, it could be proposed that significant actions are not necessary for the management of derailment risk.

It is possible to adapt the model to railway networks in different countries via an identical procedure by which mathematical-linguistic conversion took place. Nonetheless, it is necessary for experts in the field to validate the state and presence of nodes within the suggested BN in addition to reliable information sourced from incident reports and experiments. The model can potentially allow ambiguities in turnout operation management to be quantified as well as the risk of train derailments that can lead to significant destruction, network delays and even fatalities.

8.2.5 Bayesian-based hierarchical model for analysis of climate on hazardous railway component failures

This chapter examines the effect of weather patterns with distinct properties throughout the United States on these types of incidents in order to develop a scientific method of comprehending the significance of the impact of climate. This has been achieved through the detailed examination of accidents on railways with a particular focus on turnouts. Via a process of segmenting geographic regions through spatial analysis, distinct exposure levels for different areas have been discerned and applied to a Bayesian hierarchical model utilising samples via the M-H algorithm. Consequently, the thesis has produced compelling results associated with climate phenomena on the failure of turnout components causing derailed trains, by showing that it is not possible to perform meaningful research with respect to the failure estimations for larger regions characterised by severe hot and cold areas if methodology proposed in this thesis is not adopted.

This research could be perceived to initiate a new discussion topic, which is connected with analysis of railway safety, specifically derailment estimations. The analysis of railway incidents is proposed via a stochastic procedure, which provides a theoretical response to all conditions within the universe. Past literature has frequently employed a deterministic approach, which is generally restricted to the conditions based on which the research was performed. Hence, the thesis recommends that researchers studying the railway sector should implement a stochastic-based execution of issues related to railway accidents. Accordingly, a hypothesis has been devised claiming that weather has a significant effect on the frequency of failed components, based on the specific properties. Definite findings, which enhance the precision of the proposed statement have been discovered, which have a strong likelihood of assisting researchers with determining more effective estimations of derailment frequencies. This is largely due to the fact that available derailment data has been demonstrated to be ineffective at accurately estimating the frequencies for geographic regions with larger size, in which different zones are characterised by distinct climatic conditions.

This study has been performed based on instances of derailment within the railway network of the United States that were official recorded by the United States Department of Transportation. Because the railway network passes through numerous different climate regions, where the weather trends are markedly diverse, it has been possible for the researcher to determine the considerable effects of climate. Thus, it is recommended that researchers who consider derailment estimations in the future adopt the proposed methodological approach to remove the influence of weather. It is proven that this novel proposed methodology will acquire more effective results.

As a result, it is believed that the present study is applicable to railway networks with large coverage, like those in China and the European Union, so as to generate more accurate estimations. As extended plans have been developed to grow the network, it is likely that derailment frequencies will be deviated from past experiences. Conversely, a Road Safety Programme intended to produce a 50 percent reduction in railway accidents in Europe was recently implemented by the European Union. General gata throughout the EU have been recorded and will continue to be recorded by Eurostat to provide a benchmark for the EU members. These records are deterministically comparing different countries and examining any fluctuations in performance levels based on previous experience. Hence, the implementation of this study within the framework of Eurostat could generate extremely promising results. This would demonstrate the expected performance of the EU nations, based on climate variations, as well as the railway networks.

8.2.6 Railway accident analysis using large-scale investigations of train derailments on turnouts: Comparing the performances of a novel stochastic mathematical prediction and various assumptions

Due to the fact that both railway safety and the analysis of risk are dependent on the precise evaluation of the probability of derailment, specific guidelines for research into transportation are required to demonstrate how each method can be utilised in the approximation of the amount of observed derailments. The Chapter 7 has presented a novel stochastic mathematical forecasting model based on a hierarchical Bayesian model (HBM), which is more effective at addressing specific indicators of exposure in divided large-scale territories. The combination of various specialised packages, namely MATLAB for the processing of images, R for statistical analyses, and ArcGIS for illustrating and translating geospatial information, have been utilised to realise intricate solutions that can provide practical advantages to the railway sector and researchers in the field of transportation.

To facilitate smooth railway operations and effectively accomplish safety targets, there has been increased interest among railway companies and the wider public on the subject of preventing derailments associated with turnouts. The ability to predict incidents of derailment at turnouts is generally achieved via significantly complex processes of statistical analysis related to considerable possible risks. Recently, the increased cognisance of safety risk analysis as well as railway network management has made it necessary to calculate the probability of derailment, taking into account the fundamental causes, and investigating the specific types of railway exposure that have greater or lesser exposure. This research concentrates on derailments associated with component failures at RTs. Taking into account the possible effects of weather conditions on such failures, the research analyses a region within the United States that has sufficient size to conduct an investigation on derailments without having to consider changes in the weather patterns.

Various different proposals for predicting train derailments at RTs are offered within this thesis. On the basis of engineering assumptions and observations, it is possible to determine that areas where the frequency of derailment is moderate produce similar findings irrespective of whether the source of data is founded on logical assumptions or actual data. Additionally, the most vulnerable assumption is found to be the number of turnouts. The judgement of experts in the field is recommended for integrating this assumption into future analysis of failures in the context of railway engineering in addition to other similar types of railway infrastructure.

Conversely, the successful segmentation of the regions can be highlighted. The effects of weather on the failure of railway infrastructure are widely recognised. Due to the fact that this study divided a territory based on states, an effective methodological framework has been devised, thus allowing the effects of climate to be diminished. The proposed methodological approach for estimating derailments is found to be capable of overcoming the challenges surrounding derailment predictions for the segmented region.

8.3 Direction for Future Work

The research that has been performed for the purposes of this thesis has emphasised several different areas that necessitate additional investigation.

Various different topics where there is a deficiency of information were determined as a result of the review of the literature. Although some of these areas have been dealt with by the researcher in this thesis, others require further examination. In the next sections, various unresolved issues related to each of the topics addressed by this research will be presented (where work has already commenced on certain subjects). It should be noted that it is fundamentally a combination of the Future Work parts extracted from the literature review as well as novel concepts arising from various sections.

8.3.1 Deep learning of the other failure modes

Deep learning is utilised as a critical method for addressing broad sets of labelled data and neural network frameworks that include multiple layers. This method has been employed for established methodologies for three different approaches concentrating on distinctive failure modes: component failures, environmental effects and human errors.

To accomplish this objective, the thesis has endeavoured to perform independent research on a new concept and to disseminate the findings in an accessible manner to stakeholders in the railway sector via a total of 17 published studies, the majority of which form the six studies adapted as chapters of this thesis. Nevertheless, it is evident that additional analysis and novel methodologies are necessary to strengthen the understanding of the different failure modes.

It is also essential to consider standard electrical and mechanical failures for management of risk at turnouts. Before electrical connectivity was commonly available, the operation of switches that experienced dense railway trafficsss was achieved via a signal box built close to the tracks by a complex system consisting of levers and rods. Modern designs are significantly dependent on electrical motors that are controlled remotely for changing the switch system. Additionally, electrical heaters are utilised to maintain the operational temperature of rails in regions characterised by extreme cold.

In order to adopt a completely holistic approach to investigating derailment risks, it is believed that both electrical and mechanical failures have significance. Due to the fact that the thesis has been written from the perspective of civil engineering, the types of failure that are not considered within the scope of the civil engineering department have not been incorporated into the research subjects. Further to electrical and mechanical failures, it is also necessary to investigate failures associated with engines and wagons including their parts (i.e., wheels, axles), flawed wagon bodies, and draft systems.

8.3.2 Human error in railway maintenance

Human error in railway maintenance (HERM) is a topic that has not received the required focus among researchers, who conduct a comprehensive methodology. Consequently, this thesis has endeavoured to analyse these kinds of errors (excluding those related to maintenance) through the application of a new proposed methodology. The primary explanation for HERM not being included into the methodology is that there seems to be many studies that have focused on analysing and improving human factors related to train maintenance (Farrington-Darby et al., 2005, Holmgren, 2005, Holmgren and Söderholm, 2016, Itoh et al., 2004). Nevertheless, there is a deficiency in terms of observational research into any differences in the attributes of HERM between countries (and even between railway operators), as well as the relationship between them that may have happened in recent years. Future research could investigate any patterns in terms of the spatial correlation of HERM in the past decades.

Nonetheless, it is important to note that the new methodologies presented in this thesis cannot be applied to these available studies, as their methodologies is so determictic that intricate advanced methods such as sampling cannot be implemented. A multi-layer hierarchical Bayesian model (as illustrated in Chapter 4) could be recommended for followers.

8.3.3 A holistic approach for risk management

This is targeted at researchers who are enthusiastic about making additional contributions to the suggested methodologies, as an overall holistic approach has already been achieved. The previously suggested Risk Management Cycle (RMC) is shown in Chapter 1.1, (Baker et al., 1999), which illustrates the order of different stages in the risk management process, namely Identification of risk, Estimation of Risk, Evaluation of Risk, Response to Risk and Monitoring of Risk.

The initial three stages represent the most important elements of the risk management process, and require for specific complex methodologies. The thesis achieved and verified this steps through a number of unique methodologies. The thesis makes a valuable contribution to the literature due to the risk management flow ,which can be adapted for future research.

The risk management flow chart incorporates the hazard inputs and procedures required to achieve the five key pillars of the risk management circle (see Figure 1.5 in Chapter 1), as well as to increase the generalisability of the research outcomes.

The flow chart depicts various problems that are disregarded in the management circle mode, specifically:

- Reliance on hazard procedures, such as Hazard Analysis and Hazard Identification. The latter serves as the primary 'bottleneck' and obstacle preventing the identification of risks, while the former enables the risks to be estimated and evaluated of risks on the basis of suggested responses.
- Iteration and internal cycle between the estimation of risk and evaluation phases founded on the process of analysing hazards and the findings.
- Ongoing enhancement due to the continual investigation of new risks, in addition to the evaluation of already determined risks.
- There is a likelihood that divergence from the model will lead to accidents in three particular areas related to hazards: Identification of Risk, Evaluation of Risk and Monitoring of Risk.

It is possible to implement this quantitative conceptual framework for any causal group e.g. human errors and it has the potential to facilitate the process of comprehending the causal or correlational trends of interconnections across concepts, observations, ideas and other aspects of experience related to railway turnouts. Fundamentally, it refers to how reality functions, which enables predictions to be made with respect to relationship between A and B. Consequently, this guides decisions related to behaviours or experiences based on the perception of those relationships. It is important to note that the proposed conceptual framework could be significantly time consuming and can only be verified after conducting a significant amount of iterations. Hence, it can be recommended that the framework seems to be investigated by a dedicated research group.

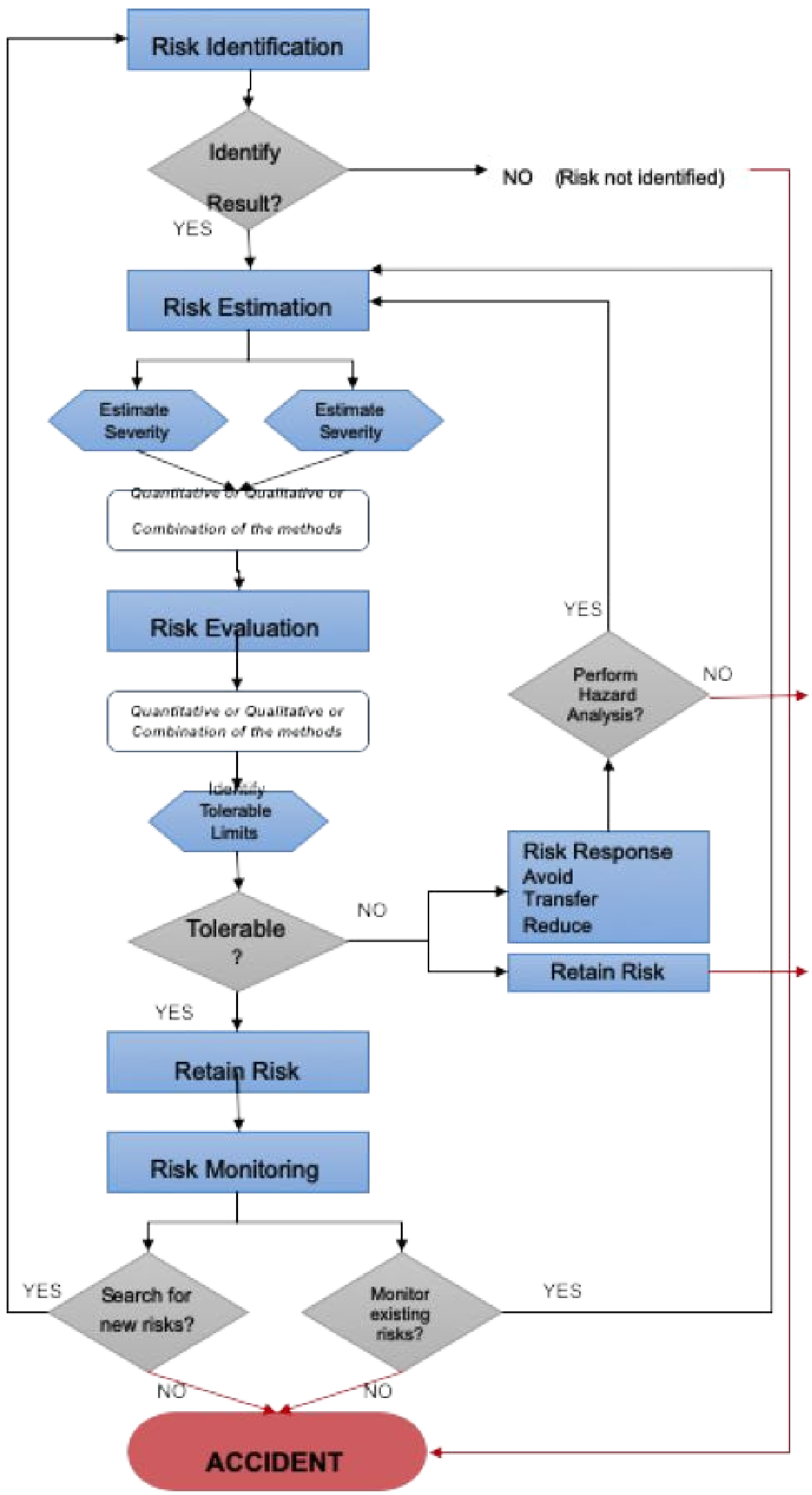

Figure 8.1: Risk Management Flow Chart.

8.4 Conclusion

The main focus of the thesis is on proposing novel methodologies to deal with various derailment causes at railway turnouts. To achieve this, Chapters 2 to 7 have been allocated by utilising data from various countries with a developed rail network, resulting in unique findings to the rail researches and industry. More clearly, the derailment causes have been identified, explained and ranked and various suggestions have been given. Moreover, the thesis also proposes a unique stochastic technique to prove relation between derailment causes.

Bayesian network is used as the thesis is more interested in Bayesian (real-locating the vast number of derailment conditions) than frequentist (revealing derailment conditions). This allows for conducting suitable studies (Chapters 2 to 7) to achieve the overall objectives and offers some advantages. Aside from the specific outcomes of the studies that have been shown at the end of each chapter and their discussion and consequences that have been underlined in Section 8.2, a summary of the main conclusions with regard to the risks of derailment and other practical issues as demonstrated by the analysis of the data can be shown as below;

- A Bayesian approach enables the use of prior knowledge (knowledge that the rail industry already has). Thus, a priori probability that is derived purely by statistical deductive reasoning has taken advantage of being modified. This allows for monitoring risk changes through the given period of time or causal relations within certain conditions, such as environmental factors. These findings and proposals might be asserted to be used for improving current railway maintenance service technique, which is based on observation by naked eye or tools, and on checking within given intervals.

- Robustness of the proposed risk models has been provided, as Bayesian analysis is commonly known to be quite robust to outliers. Chapters 6 and 7, which are based on samples generated by Metropolis-Hasting algorithm, are observed to benefit from this robustness. The kernel probability distributions formed of the generated samples have been compared to the real observations. It is seen that the estimates are quite precise.

- Bayesian analysis is observed to tie suitably into multi-step strategies. Chapters 4 and 5 provide novel risk analysis methodologies on the basis of a Bayesian network. Root nodes and intermediate nodes (derailment causes) are observed to respond to such methodologies. On the other hand, Chapters 6 and 7 are structured through a multi-layer hierarchical Bayesian model. It is found that a hierarchical structure for derailment investigation offers quite satisfying results to risk investigations of railway accidents.

- In contrast to common belief on frequentist approaches to suit the falsification of a hypothesis, or vice versa, it is ascertained that Bayesian analysis offers better estimates in certain methodological conditions. Chapter 7 proposes a novel hypothesis and proves it by utilising the previously developed complex and distinctive stochastic risk model, which underlies the considerable computational and scientific innovation that does not exist in the current literature. As a result of this stochastic risk model, it is observed that the stochastic-based Bayesian analysis proves mathematically the proposed hypothesis. Subsequently, the real observations are found out to support this mathematical assertation.

In conclusion, the thesis can be emphasised to offer various kinds of novel ideas and methodologies to the railway industry. The derailment causes associated with turnout component failures, human factors and environmental conditions have been identified, analysed and prioritised through these proposed novel ideas and methodologies. Moreover, the thesis illustrates how to manage two causes together to identify a hidden relation between them, which is a novel field in railway risk management, particularly as related to the subject of railway accident analysis. Considering the identification of a greater relation between causal groups, the first steps of a fully AI-based potential neural network have been provided. The following studies associated with risk research in this field can be considered to benefit from the primary studies as presented through the thesis.

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Contents for Appendices