Improving Railway Safety Risk Assessment Study

by

Mr YAO CHEN

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ABSTRACT

Railway safety is very important, as it concerns human lives. Therefore identifying risks from possible failures is vital to maintain the safety of railways. Currently, many mature tools, such as fault tree analysis and event tree analysis, are applied to investigate possible risks to railway safety. However, in many circumstances, the applications of these tools are unable to provide satisfactory results when the risk data is incomplete or there is a high level of uncertainty involved in the risk dataThus it is essential to develop new methods to overcome the weakness of current assessment tools. This thesis introduces an improved intelligent system for risk analysis usingfuzzy reasoning approach (FRA) and improved fuzzy analytical hierarchy decision making process (Fuzzy-AHP), which is specially designed and developed for the railways, and able to deal with the uncertainty in risk assessment. The system builds upon work carried out by Dr Huang Shen who developed a safety risk model using FRA and Fuzzy-AHP. In his model, the risk level (RL) is assessed in terms of failure frequency (FF) and consequence severity (CS). This research introduced consequence probability (CP), which allows risk to be assessed correctly. In this system, FRA is employed to estimate the risk level (RL) in terms of FF, CS and CP. This allows imprecise or approximate information to be used in the risk analysis process. Improved Fuzzy-AHP technique is then integrated to determine the relative importance of risk contributors, so that the risk assessment can be progressed from hazardous event level to hazard group levels and finally to railway system level. Additionally, in order to select cost-effective measures to minimise the risk, a risk-based maintenance decision making model is developed by using the technique for preference by similarity to the ideal solution (TOPSIS) method which synthesises the proposed risk and cost models to produce the preference degree of each maintenance option. Both the risks associated with a railway asset and the costs incurred in each maintenance option are mapped onto a utility space and assessed in accordance with the respective constraints. The proposed decision making model could be an effective tool to get a better understanding of risks associated with railway assets and make better maintenance decisions at the right time for managing the risks under various conditions. Two case studies are conducted to demonstrate the potential benefits of the methodology.

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ABBREVIATIONS

AHP	Analytical Hierarchy Process
AI	Absolute importance
ALARP	As Low As Reasonably Practicable
BEW	Between equal and weak importance
BSV	Between strong and very strong importance
BVA	Between very strong and absolute importance
BWS	Between weak and strong importance
CHG	Collision hazard group
CS	Consequence severity
CP	Consequence probability
DHG	Derailment hazard group
EFA	Equivalent fatality analysis
EHG	Electrocution hazard group
EI	Expert index
EQ	Equal importance
ETA	Event tree analysis
FEM	Fuzzy Estimation Module
FF	Failure frequency
FHG	Falls from height hazard group
FL	Failure likelihood
FMEA	Failure mode and effect analysis
FRA	Fuzzy reasoning approach
FTA	Fault tree analysis
Fuzzy-AHP	Fuzzy analytical hierarchy process
FWM	Fuzzy Weighting Module
HAZOP	Hazard and operability

HG	Hazard group
HSE	Health & Safety Executive
ISO	International Organisation for Standardisation
LUL	London Underground Ltd
MF	Membership function
MCDM	Multi-criteria decision making
ODBC	Open Database Connectivity
OM	Output Module
PHA	Preliminary Hazard Analysis
PRA	Probabilistic risk analysis
QRA	Quantified risk assessment
RL	Risk level
RISRAS	Railway intelligent safety risk assessment system
RTM	Risk Tree Module
RSSB	Rail Safety and Standard Board
SHG	Slips/trips hazard group
SI	Strong importance
SMART	Simple Multi-attribute Rating Technique
SRM	Safety Risk Model
TfHG	Train fire hazard group
TOPSIS	Technique for preference by similarity to the ideal solution
TsHG	Train strikes person hazard group
UFN	Uniform Format Number
VI	Very strong importance
WF	Weight factor
WI	Weak importance
WPM	Weighted Product Model
WSM	Weight Sum Model

CHAPTER 1: INTRODUCTION

1.1 Background

Risk, in the railway sector, can be defined in relation to accidents and incidents leading to fatalities or injuries of passengers and employees (Profillidis, 2006). Recent structured hazard identification work within the industry has confirmed high-risk scenarios of the types of accidents such as collision, derailment and fire (Peter et al., 2006). The statistics of accidents and incidents include not only workers, but also a significant number of people not employed in the industry, including children and members of the public. In the UK railway industry, many people have been injured and there even have been fatalities in past years (LUL, 2001). This shows the dangerous nature of the railway industry and demonstrates the need for increased awareness and better safety management (Muttram, 2002). To achieve how that can be assessed effectively, knowledge of the nature and causes of these accidents are fundamental. Therefore, risk analysis plays a central role in the railway safety management framework. The most common hazards in railway system identified by the railway industry over the years (LUL, 2001; Railway Safety, 2002; Metronet, 2005) provide very useful information for risk analysis, for example, derailment hazards, collision hazards, fire hazards, electrocution hazards, fall hazards, train strike hazards, slip/trip hazards, and platform/train interface hazards. The requirement of risk analysis is to demonstrate that: if risks associated with a railway system are high, risk reduction measures must be applied or operation and maintenance have to be reconsidered to reduce the occurrence probabilities or control the possible consequences; if risks are negligible, no actions are required but the information produced needs to be recorded for audit purposes (An et al, 2008; HSE, 2000). Therefore railway engineers, managers and safety analysts need to develop and employ risk assessment approaches for safety management and set safety standards.

Many risk assessment techniques currently used in the railway industry are comparatively mature tools, which have been developed on the basis of probabilistic risk analysis (PRA), for example, fault tree analysis, event tree analysis, Monte–Carlo simulation, consequence analysis and equivalent fatality analysis (EFA) (LUL, 2001; Railway Safety, 2002; Metronet, 2005; An et al., 2011). The results of using these tools heavily rely on the availability and accuracy of the risk data (LUL, 2001; Railway Safety, 2002; Metronet, 2005). However, in many circumstances, these methods often do not cope well with uncertainty of information. Furthermore, the statistic data does not exist and it must be estimated on the basis of expert knowledge and experience or engineering judgement. Therefore railway risk analysts often face circumstances where the risk data are incomplete or there is a high level of uncertainty involved in the risk data (An et al., 2011). Additionally, railways are a traditional industry, whose history extends for at least two centuries. Much of the safety record of the railways depends upon the concepts developed many years ago and established practices over the whole of its history. The existing databases contain a lot of data and information, however, the information may be both an excess of other information that cannot be used in risk analysis or a shortage of key information of major failure events. There are numerous variables interacting in a complex manner which cannot be explicitly described by an algorithm, a set of equations or a set of rules. In many circumstances, it may be extremely difficult to conduct PRA to assess the failure frequency of hazards, the probability and the magnitude of their possible consequences, because of the uncertainty in the risk data. Although some work has been conducted in this field, no formal risk analysis tools have been developed and applied to a stable environment in the railway industry (Chen et al., 2007). Therefore it is essential to develop new risk analysis methods to identify major hazards and assess the associated risks in an acceptable way in various environments where those mature tools cannot be effectively or efficiently applied. The railway safety problem is appropriate for examination by FRA and fuzzy-AHP.

Usually, the magnitude of a risk can be assessed by considering two fundamental risk parameters: failure frequency (FF) and consequence severity (CS) (An et al, 2006). The FF defines the number of times that an event occurs over a specified period, e.g. number events/year. The CS represents the number of fatalities, major injuries and minor injuries resulting from the occurrence of a particular hazardous event. However, it should be noted that the magnitude of a particular risk also highly depends on the probability that the effects will happen given by the occurrence of the failure. Therefore the probability of a current consequence caused by a particular failure should be taken into consideration in the risk assessment process to obtain a reliable result. In order to assess the risks associated with a railway depot efficiently and effectively, a new risk parameter, consequence probability (CP) is introduced in the proposed risk analysis model to determine the risk level (RL) of a hazardous event. The use of FRA allows imprecision or approximate information involved in the risk assessment process (Bojadziev et al., 1997; An et al., 2006). In this method, a membership function (MF) is regarded as a possibility distribution based on a proposed theory; an apparent possibility distribution expressed by fuzzy set theory is transferred into a possibility measure distribution. The FRA method provides a useful tool for modelling risks and other risk parameters for risk analysis involving risks with incomplete or redundant safety information. Because the contribution of each hazardous event to the safety of a railway system is different, the weight of the contribution of each hazardous event should be taken into consideration in order to represent its relative contribution to the RL of the railway system. Therefore the weight factor (WF) is introduced, which indicates the magnitude of the relevant importance of a hazardous event or hazard group to its belongings in a risk tree. Modified fuzzy-AHP has been developed and then employed to calculate the WFs (Chen et al, 2011). This has been proved to facilitate the use of fuzzy-AHP and provide relevant reliable results. This thesis presents a development of a railway risk assessment system using FRA and modified fuzzy-AHP. The outcomes of risk assessment are represented as risk degrees, defined risk categories of RLs with a belief of percentage, and risk contributions. They provide safety analysts, managers, engineers and decision makers with useful information to improve safety management and set safety standards.

As stated earlier in this Chapter, if risks are high, risk reduction measures must be applied or maintenance work must be considered to reduce the occurrence probabilities or control the possible consequences. If risks are negligible, no actions are required，but the information produced needs to be recorded for audit purposes. However, the acceptable and unacceptable regions are usually divided by a transition region. Risks that fall in this transition region need to be reduced to as low as reasonably practicable (ALARP). In other words, “cost-effective” measures should be applied. In this case, selecting the optimal maintenance strategy among many alternatives based on cost and safety analysis is a multi-criteria decision making (MCDM) problem, which can usually be solved by optimisation techniques. The literature search indicates that traditional cost-benefit analysis based on simple comparisons cannot be applied to this process. This study also presents a risk-based maintenance decision making model by using the TOPSIS technique which synthesises the risk and cost models to produce the preference degree of each maintenance option. Once preference degrees of all maintenance options in hand are produced, the best option can be chosen. In this model, both the risk associated with a railway asset system and the costs incurred in each maintenance option are mapped onto a utility space and assessed in accordance with the respective constraints. The proposed decision making model could be an effective tool to get a better understanding of risks associated with railway asset systems and make better maintenance decisions at the right time for managing the risks under various conditions.

1.2 Aims

The primary aim of this study is to develop and improve railway safety risk models further in order to meet the needs of industry and to apply the safety risk prediction system in a real environment with industry partners. In particular, this system could be applied to define risks and the numerical levels of expectation. This will support the industry's efforts to run the rail network with normal service while keeping risks ALARP. This project also sets out to facilitate effective maintenance planning for railway vehicle and infrastructure operators, engineers and health & safety advisors. The secondary aim is to investigate how intelligent safety analysis techniques can provide insights into the ways that risks contribute to accidents, for example, collisions, derailments and fires, via case studies and the determination of the most appropriate maintenance for various conditions. Therefore, The study is

- To: enable improved safety through design, diagnosis and maintenance of railway systems.
- For: rail vehicles, infrastructure operators, track & civil engineering designers and maintainers, as well as health & safety advisors.
- By: developing safety risk models and tools using FRA and AHP techniques to railway safety risk assessment and decision making processes.

1.3 Objectives

The specific objectives of this research project are:

1 To investigate further railway safety risk assessment tools as used in practice and in research literature worldwide.

2 To develop further railway safety risk models and tools to facilitate railway safety risk analysis. Safety risk models based on FRA combined with AHP techniques will be established for processing safety risk assessment efficiently and effectively.

3 To validate the proposed railway safety risk system via case studies with industrial partners.

4 To develop a risk-cost model to assist railway maintenance decision making.

5 To apply the proposed methodology and tool to a railway maintenance strategy study.

1.4 Research Methodology

The metrologies during the research life-cycle are presented in Figure 1-1. The research will start with the selection of the subject, aim, objectives and research methodologies in general. And then a comprehensive literature review will be carried out on risk assessment methods, decision-making approaches and current applications in practice. After that, an improved railway safety risk model and risk-based decision making will be developed, reviewed and improved through literature review, interviews and publications. In the meantime, a prototype of software tool will be developed as well. Finally, the application of above approaches will be placed at the end of each developing cycle. The following stages are summarized as the followings:

1 Review of relevant literature on railway safety risk assessment techniques and decision-making approaches. The major parameters (rail & vehicles) that influence the decisions concerning which maintenance option is selected will be studied in detail. The techniques used to select a maintenance option based on cost and safety risk analysis will be reviewed. All the selection processes will be studied in detail, together with the level of confidence associated with decision making.

2 Development of safety risk assessment approaches for facilitating railway safety risk analysis. The safety risk assessment model will be developed based on FRA Fuzzy-AHP techniques to facilitate risk analysis where there is a high level of uncertainty or data incomplete.

3 Prototype software tool. A prototype software tool will be developed which will be compatible with a PC platform in C++. Case study materials will be obtained from industrial partners to test the developed system in order to enable the system can be used in practice efficiently and effectively; which can also be developed further by a partner into commercial software.

4 Development of advanced maintenance procedures to minimise risks. Multi-objective decision-making techniques will be investigated in order to select the best solution for railway maintenance decision making.

5 Application of the above approaches to a railway safety case. The developed safety risk analysis models and software system will be applied to a railway operation and maintenance study.

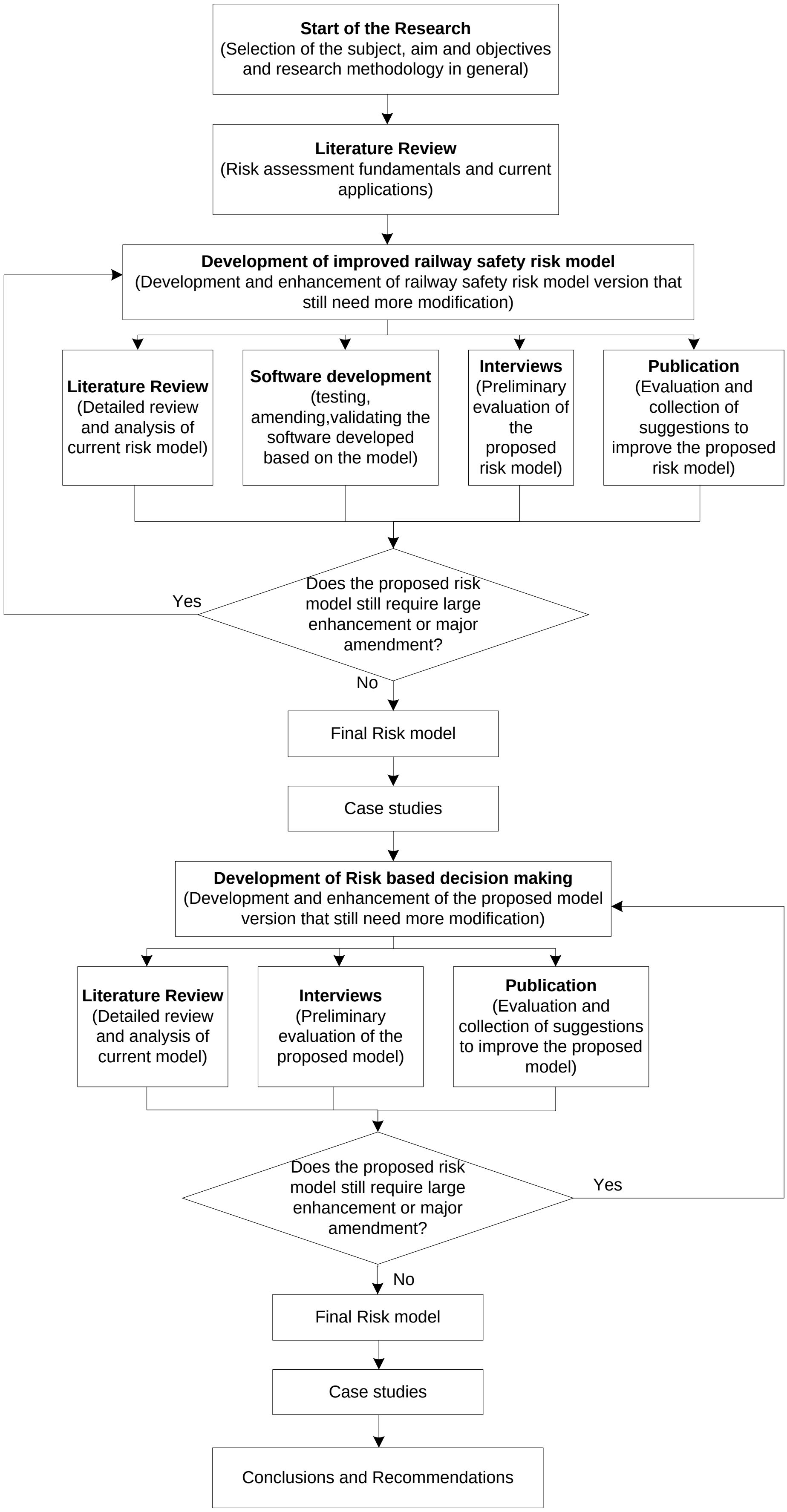


Figure 1-1 Research approach

1.5 Research outcomes

The research outcomes are:

- Literature survey and benchmark reports of current best practice for safety risk assessment in the railway industry. Flow charts showing comparative safety risk assessment processes for railway by conventional (statistical and probabilistic) techniques, fuzzy reasoning techniques and expert inputs.
- Safety risk assessment models for the issues where prediction is currently weakened by inadequate or inconsistent data.
- A robust safety risk analysis framework that will provide a platform where risks associated with the railway system can be assessed effectively and efficiently, so that railway maintenance decisions can be made.
- A supporting prototype software to facilitate the application of the anticipated approaches.
- A risk based decision making system that will provide decision makers very useful information for their decisions on maintenance options or strategies.

In addition, five research papers have been published at international conferences and in academic journals. They are:

1. M. An, Y. Chen and C. J. Baker, 2011. *A fuzzy reasoning and fuzzy-analytical hierarchy process based approach to the process of railway risk information: A railway risk management system*. Information Sciences, 181(18), 3946-3966. (Please see Appendix)
2. Y. Chen, M. An, 2011. *Application of a modified Fuzzy-AHP methodology to railway risk decision making process*. Proceedings of the International Railway Engineering Conference (REC 2011), CD format, London, UK, ISBN 0-947644-69-5.
3. M. An, Y. Chen, C. J. Baker, 2008. *Development of an intelligent system for railway risk analysis*. Proceeding of 3rd International Conference on System

Safety, ISBN 0-479622-23-13, pp.1-6.

4. S. Huang, M. An, Y. Chen, C. J. Baker, 2007. *Railway safety risk assessment using FRA and fuzzy AHP approaches – a case study on risk analysis of shunting at Waterloo depot*. Proceedings of the 2nd IET International Conference on System Safety, London, UK., pp. 35-38
5. Y. Chen, M. An, S. Huang, C. J. Baker, 2007. Application of FRA and FAHP approaches to railway maintenance safety risk assessment process. Proceedings of the 9th International Railway Engineering, CD format, ISBN 0-947644-61–10.

1.6 Structure of the Thesis

The thesis is organised into nine chapters. Chapter 1 is the introduction to this study including aim and objectives of the research project and research methodologies adopted in the study.

Chapter 2 then reviews railway safety issues, top-down and bottom-up risk assessment approaches, and current railway safety risk assessment methods including qualitative, semi-qualitative and quantitative approaches.

Chapter 3 discusses the concept of fuzzy expression covering fuzzy set and fuzzy number. The fundamentals of FRA and Fuzzy-AHP in terms of fuzzy expression are outlined. Finally, a modified Fuzzy AHP is introduced in this chapter.

Chapter 4 presents the development of an improved railway safety risk model by using the modified Fuzzy-AHP approach. The process of such a railway safety risk assessment model at each phase is described and a third parameter, CP, is introduced.

Chapter 5 describes the software development based on the proposed railway safety risk model including detailed design of logic layers, features and application of this software in railway safety risk assessment.

Chapter 6 presents the development of a new risk-based decision making approach. It involves a safety risk model, a cost model and a risk-cost model. The TOPSIS approach is applied to optimise the selection of maintenance options in terms of risk and cost.

Chapters 7 and 8 present two case studies collected from railway industry: risk assessment of shunting at Hammersmith depot and risk assessment of a track system, by applying the proposed safety risk model and risk based decision making approach. The results indicate that the railway safety risk can be assessed more efficiently and effectively by using the proposed methodologies.

Finally, Chapter 9 concludes the main benefits of using the developed railway safety risk model. Many interesting findings lead to some recommendations for further works which are suggested at the end.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter reviews and discusses potential problems related to railway safety and major types of railway accidents. The definitions of risk and risk assessment are also discussed. And top-down and bottom-up risk assessment approaches are described. The qualitative, semi-quantitative and quantitative risk assessments are discussed as well, which will form the basis of the development of new risk assessment techniques.

2.2 Railway Safety

While the safety level of rail transport is far higher than other transport modes, there exist possibilities to further enhance railway safety. According to the International Organisation for Standardisation (ISO), safety can be defined as the release from unacceptable risks, a risk being a combination of probability and of gravity of harm. In the railway sector, the risk can be defined in relation to the events that damage safety (fatalities or injuries of passengers or employees) or transportation stability (delay) (Profillidis, 2006).

2.2.1 Potential safety problems

In order to avoid accidents, appropriate railway maintenance and safety measures should be put in place after suitable investigations to provide safe and economical train transportation (Rasaiah, 2002). However, railway science is a complicated subject, which is interdisciplinary and requires competences of civil engineers, economists, electrical and mechanical engineers and managers. Thus, following railway network reorganisation, it has become customary to distinguish railway science into three topic areas (Profillidis, 2006):

(1) Track topics: subjects concerning railway infrastructure are dealt with, in order to

ensure the safe operation of the rolling stock at the scheduled speed. The superstructure (e.g. rails, sleepers, fastenings, ballast or concrete slab) and the subgrade are central subjects of track topics. Track topics also include layout, stations, switches and crossing, maintenance and safety issues.

(2) Traction topics: subjects concerning rolling stock are elaborated on. Traction topics also include electric traction, telecommunications and signaling; however, a certain railway includes these in the area of track topics, since they are parts of the permanent railway infrastructure.

(3) Operation topics: including commercial operations in which commercial and pricing policies are analysed and technical operations where issues concerning schedule organisation and optimum use of rolling stock and traffic safety are examined.

To the above should be added the topic of metropolitan railways (metros and tramways), which constitute a specific railway class of their own great importance to mass transit in large urban centres. However, after separation from operation, track topics, electrification, telecommunication, signalling, and technical operations belong to the responsibilities of infrastructure controllers, whereas rolling stock operation and maintenance and commercial operation belong to the responsibilities of railway operators. Railway stations may be studied either in infrastructure or operation, depending on where the station best belongs.

Railway science is, therefore, a complicated subject which is interdisciplinary and requires competences from the sectors of civil engineering, economics, electrical and mechanical engineering and management. The hazard checklist for railways could list the potential hazards in such areas. It has to include mechanical hazards, electrical hazards, thermal hazards, thermodynamic hazards, hazards generated by noise, hazards generated by vibration, hazards generated by materials/substances, and environmental hazards (Profillidis, 2006). For example, electrical hazards include persons contact live parts (direct contact), contact between a person and parts which have become live under faulty conditions (indirect contact), approaching live parts under high voltage, and thermal radiation or other phenomena such as the projection of molden particles and chemical effects from short circuits, overloads, etc. Thermal hazards include burns, scalds and other injuries by a possible contact between a person and objects or materials with an extremely high or low temperature, by flames or explosions and also by radiation of heat sources, and damage to health from a hot or cold working environment etc.

2.2.2 Major types of railway accidents

Accidents are the results of complicated combinations of various factors such as the number of trains, the number of passengers and freight, safety equipment (signalling and speed control), the surrounding environment and human factors. Usual forms of rail accidents are: collision, derailment, fire, accidents during maintenance works, with pedestrians at platforms, and etc. There are five major types of structurally significant accidents in the United Kingdom (Rasaiah, 2002) which are end-on collisions, side-on collisions, buffer stop collisions, level crossing collisions and derailments (including those caused by obstacle strikes, broken rails and running gear).

For example, in a topical railway depot, accidents and incidents can be categorised into ten groups as(Metronet, 2005):

(1) The derailment hazard group, which consists of a number of hazardous events such as: track related faults including mechanical failure of track, e.g. broken rail and fishplates; signalling related faults including mechanical failure of signals and points; rolling stock faults including mechanical failure of rolling stock, e.g. brakes, axles and bogies; structure failure including collapsed drain or civil structure beneath track leading to derailment; object from a train including object falling from a train (e.g. motor) leading to derailment (such as the Chancery Lane incident); human error including human error causing derailment, e.g. speeding, incorrect routing, etc.

(2) The collision hazard group, which includes collision between trains and collision

hazards. Collision hazards include events such as: a collision with an object on a track; collision with a terminal, e.g. overrunning at the end of any of the depot roads; collision with platforms involving both the track and/or the train being out of gauge without anybody noticing it; collision with other civil structures involving track/train being out of gauge and nobody noticing.

(3) The train fire hazard group includes events of arcing from the conductor rail causing train fire, and electrical, oil or hydraulic failure leading to train fire.

(4) The electrocution hazard group covers a number of hazardous events, for example: contact with the conductor rail while entering/leaving cab; contact with the conductor rail while walking to the train; plugging in gap jumper leads if the train is stalled/gapped; flooding, e.g. sumps or pumps leading to surface water; and conducting electricity from conductor rails, etc.

(5) The slips/trips hazard group includes, for example, instances when the shunter is required to leave train and risks to other persons involved in the move and instances when a person is required to approach the train when it is stalled/gapped.

(6) The falls from height hazard group covers falls from a height, such as when a shunter leaves the train cab.

(7) The train strikes person hazard group covers events where a train strikes an authorized person including other depot workers (e.g. ground shunter) or track side staff and where the train strikes an unauthorized person, e.g. trespassers, etc.

(8) The platform train interface hazard group, which covers the train hitting a person on the platform. For example, train moves will not take place with passengers present (either outside of passenger hours or when the platform is closed for a move). Persons are considered at risk including station staff and contractors.

(9) The structural failure hazard group, in which the hazardous events cover scenarios of partial or catastrophic collapse of structures the hitting train, e.g. wall collapse, train wash collapse, ceiling collapse and cables/pipes becoming loose, etc.

(10) The health hazard group includes hazardous events such as the failure of pumps and sumps leading to flooding and health hazards posed by mercury and arsenic in ballast that would be washed to surface.

In order to minimise risk, railway safety risk assessments need to be carried out. If a risk event falls into a high risk band, risk reduction measures must be applied or maintenance work has to be considered to reduce the occurrence probabilities of the risk event, or to control its possible consequences. If a risk event falls into a negligible risk band, no actions are required but the information produced from risk assessment needs to be recorded for audit purposes (An et al., 2006 & 2007).

2.3 Overview of Railway Safety Risk Assessment

2.3.1 Definitions

Risk is defined as:

- "Risk is the combination of the probability of an event and its consequences," (ISO, 1999);
- "Risk is the likelihood that a hazard will actually cause its adverse effects, together with a measure of the effect," (HSE, 2005).

It can be seen that a risk is a certain hazard occurring and its adverse consequences. Risk management is defined as the culture, process and structures that are directed towards the effective management of potential opportunities and adverse effects (Rausand et al., 2004). Figure 2-1 shows a risk management system. The risk management process is the systematic application of management policies, procedures and practices to the tasks of establishing the context, identifying, analysing, evaluating, treating, monitoring and communicating the risk.

Risk assessment is an essential part within risk management system. It includes an overall process of risk analysis and risk evaluation. Risk analysis is the systematic use of available information to identify hazards and to estimate the risks of a railway system. Risk evaluation is a process to determine risk management priorities by comparing the level of a risk against predetermined standards, target risk levels or other criteria, e.g. HSE safety risk regulations.

With railways, especially for railway safety management and railway safety case preparation, risk is assessed in the context of safety. Railway safety risk assessment is based on an assessment of the risk resulting from hazardous events which can occur as a result of the duty holder's operations which have the potential to lead to fatalities, major or minor injuries to passengers, staff or members of the public. It is an important tool to aid decision-making, thus it is an important part of successful railway safety risk management.

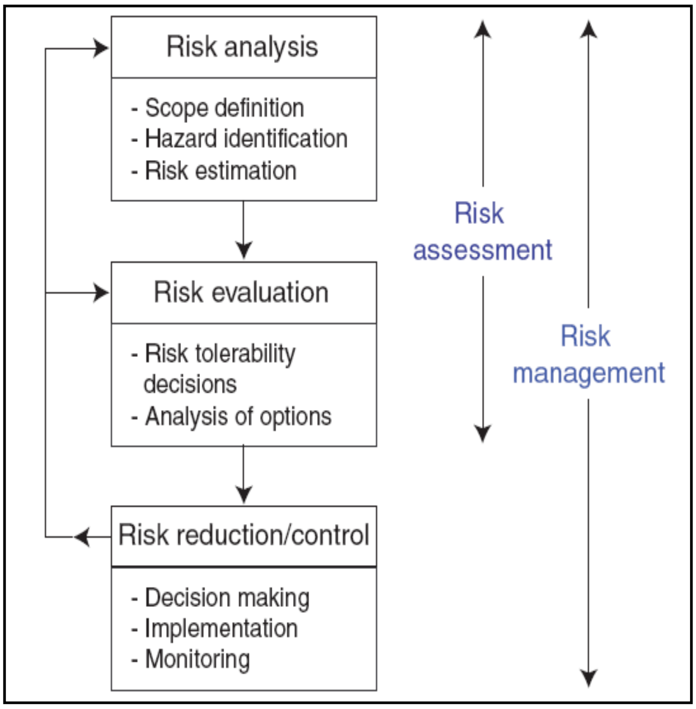


Figure 2-1 Risk management (Rausand et al., 2004)

2.3.2 Current risk assessment

The Management of Health and Safety at Work Regulations 1974 require employers to assess the health and safety risks involved in all work activities. Nowadays, risk assessment is a common requirement of all health and safety legislation. The emphasis is now on preventing accidents and work-related ill health, rather than just reacting to incidents and making improvements after the event. Currently, a typical risk assessment is usually divided into three phases: hazard identification, risk estimation and risk response.

The hazard identification phase seeks to identify the risks to be managed. Comprehensive identification using a well-structured systematic process is critical because a risk that has not been identified cannot be managed risk is assessed in the context of safety. The aim of hazard identification is to generate a comprehensive list of sources of risks and events that might have an impact on the achievement of each objective identified in the context. The most popular techniques used to identify hazards include checklists, expert and engineering judgements, brainstorming approach, system analysis, scenario analysis etc. (AS/NZS, 1999). The application of these techniques will depend on the nature of the activities under review, types of risks, the organisational context and the purpose of the risk management (Rausand et al., 2004).

In the risk estimation phase, risk is estimated and evaluated on the basis of likelihoods and consequences of hazardous events identified in the hazard identification phase. A qualitative, or semi-quantitative, or quantitative risk assessment or a combination of these three may be applied to evaluate risk level of each hazard event depending on the circumstances. Various risk analysis techniques might be used, such as fault tree analysis (FTA) (Vesely et al., 1981), event tree analysis (ETA) (Crawley and Tyler, 2003), FMEA (Stamats, 1995), HAZOP (Crawley and Tyler, 2000), fuzzy reasoning approach (FRA) and fuzzy analytical hierarchy process (AHP) (An et al., 2006 & 2007). The application of these techniques will also depend on the availability of information required during risk analysis. For example, if there is a great uncertainty involved in the risk data, FTA and ETA may not be suitable to use, whereas FRA and fuzzy AHP will be appropriate, which will be discussed later in this thesis.

The purpose of the risk response phase is to make decisions, based on the outcomes of the risk estimation, about which risks need a treatment and treatment priorities. The risk response phase involves comparing the level of risk found during the analysis process with risk criteria established when the context was considered. The objectives of the organisation and the extent of opportunity that could result should be considered. Where a choice is to be made between options, higher potential losses may be associated with higher potential gains and the appropriate choice will depend on an organisation's context. If risks are high, risk reduction measures must be applied or maintenance work has to be considered to reduce the occurrence probabilities or to control the possible consequences. If risks are negligible, no actions are required but the information produced needs to be recorded for audit purposes. These two circumstances are categorised respectively into the unacceptable region and the acceptable region. There is usually a transition region between these two regions. A risk that falls within this transition region needs to be reduced to ALARP. All railway duty holders are required to manage and reduce risks to ALARP to ensure the safety of staff, passengers and the publics.

2.3.3 Top-down and bottom-up risk assessment approaches

Railway safety risk analysis is a complex subject. Efficient use of risk analysis methods in the risk assessment process involves the study of the characteristics of each risk analysis method and assessment process in terms of the way in which risk analysis is carried out. A safety risk assessment method may be classified as either a top-down approach or a bottom-up approach by studying the way in which risks associated with a railway system are identified (An et al, 2000, 2006 and 2007; Wang et al, 1998).

Railway safety risk analysis may be summarised to answer the following four questions (An et al., 2000a; Hashemi et al., 1995; Wang, 1998):

1. What can go wrong?
2. What are the effects and consequences?
3. How often will they happen?
4. What measures need to be undertaken to reduce the risks and how this be achieved?

To answer the above questions, an actual railway system must be examined to identify and assess potential hazardous situations and associated risks in order to provide a rational basis for determining where risk reduction measures are required.

Either a top-down or a bottom-up safety risk analysis approach can be used to identify accident scenarios. The decision as to which kind of analysis is more appropriate is dependent on the availability of the safety risk data and information of the railway system being studied, the indenture level of analysis required, the degree of complexity of the inter-relationships of the components and sub-systems, and the level of innovation.

2.3.3.1. Top-down risk assessment approach

A top-down safety risk assessment process, as shown in Figure 2-2, starts with the study of previous accident and incident reports. After the top events which must be studied further have been determined, the causes leading to them are then identified deductively in increasing detail until all of the causes are identified at the required level of resolution. In a top-down safety risk assessment approach, both qualitative analysis and quantitative analysis can be carried out to estimate and evaluate risks regarding the demand for safety. A risk response can then be undertaken by making use of the information produced from the safety risk assessment, to close the loop of the risk assessment process.

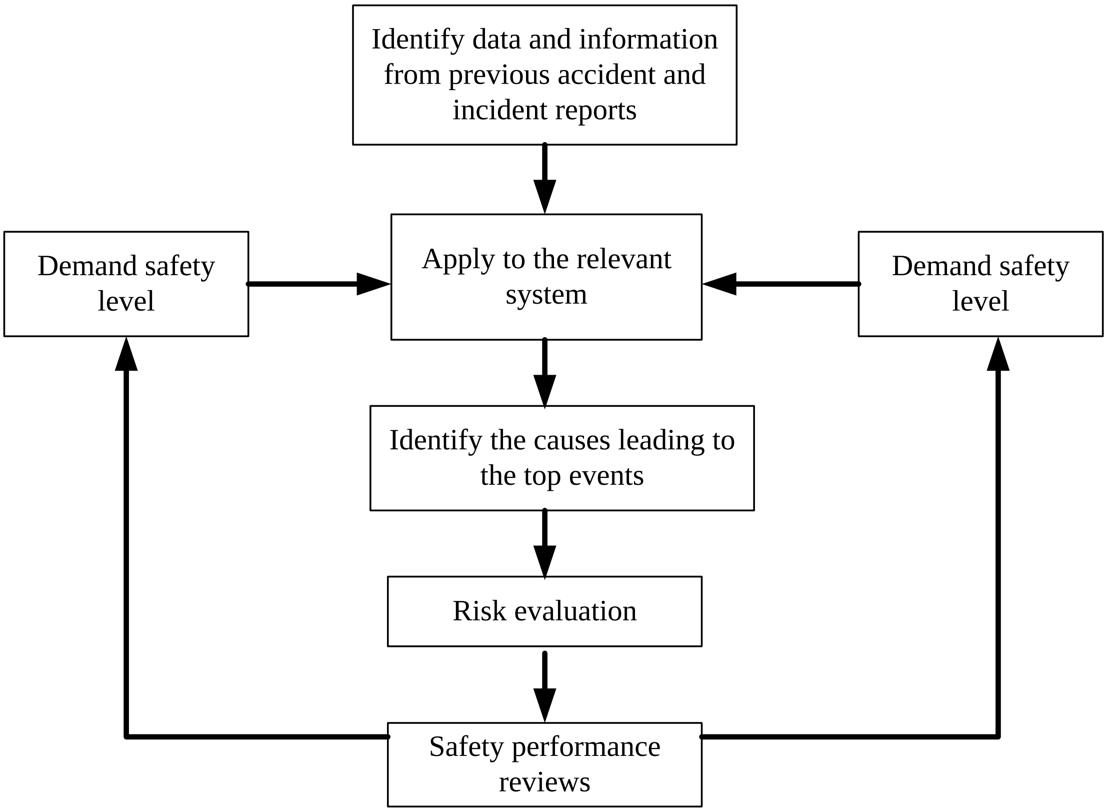


Figure 2-2 A top-down safety risk assessment process (An et al, 2000a and b)

For simple systems, a top-down risk assessment approach may prove convenience and time-saving, because it only deals with failure paths leading to particularly serious system failure events by studying the relationships of the subsystems and components, and the risk data from previous accidents and incident reports of similar systems. Obviously, experience, good judgement and understanding of the system are very important for an efficient and effective use of this approach.

However, for large systems such as a railway system, there will often be a lack of knowledge or experience regarding the determined system solutions and their possible effects on safety. In such a case, the top-down approach may have the following problems (Wang, 1997; An et al., 2000a and b):

- data and information may not be available from previous accident and incident reports of similar systems;
- there may be a lack of confidence that all failure causes associated with the top events are completely identified;

- deductive characteristics in a top-down safety risk assessment process may not address the complex interactions present in a complex system in a rigorous way.

Therefore, a bottom-up risk assessment approach is required.

2.3.3.2. Bottom-up risk assessment approach

In a bottom-up safety risk assessment process, a system to be analysed can be broken down into subsystems which can be further broken down to components in order to identify all possible hazards. The hazard identification can be initially carried out at the component level, and then progressed firstly up to the subsystem level and finally to the system level. All combinations of possible failure events at both of the component and the subsystem levels may be studied to identify all the possible system failure events. The analysis at subsystem level may make use of the information produced at the component level. Finally, risk evaluation and review can be conducted.

A bottom-up risk assessment process is shown in Figure 2-3. In this approach, risk assessment can be initially carried out at the component level, and then progressed up to the subsystem level and finally to the system level. Risk estimation can also be conducted in a similar manner. The information produced from the risk estimation phase can be evaluated together with a risk review.

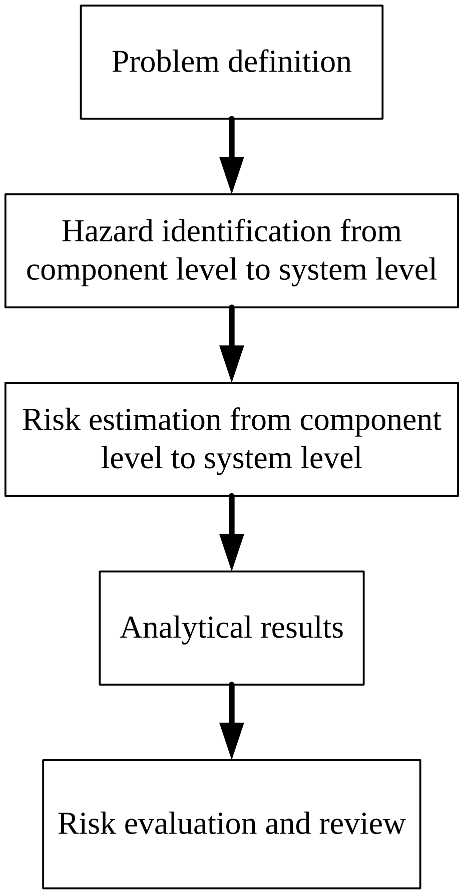


Figure 2-3 A bottom-up assessment approach (An et al, 2000a and b)

The use of a bottom-up risk assessment process yields a higher level of confidence that all of the failure events of a railway system and their respective causes are identified. Therefore, compared with the top-down approach, the bottom-up approach has the following characteristics (Wang 1997, An et al. 2000a and b):

- omission of system failure events and their respective causes are less likely;
- it may be more convenient to incorporate into a computer package;
- it may be more suitable to apply to safety risk analysis of a large railway system with a high level of uncertainty.

In railway safety risk analysis, the risk assessment of a railway system is often a hierarchical process where risk assessments at higher levels (i.e. system) are determined by the safety risk assessment at lower levels (i.e. component/subsystem). Therefore, a hierarchical procedure is required to synthesise the information produced at lower levels to obtain the safety risk assessment at a high level of the system. A bottom-up safety risk assessment approach may be more appropriate to be employed in the development of a safety risk assessment model. The use of a bottom-up safety risk assessment approach can obtain a higher level of confidence that all of the failure events of a railway system and their respective causes are identified. Therefore, the development of a railway safety risk model adopts a bottom-up safety risk assessment process. Details of the developed railway safety risk model are described in Chapter 4.

2.3.4 Quantitative and qualitative railway safety risk assessments

Risk assessment may be undertaken to varying degrees of detail depending upon the risk, the purpose of the analysis, and the information, data and resources available (AS/NZS, 1999). Thus, assessment may be quantitative, qualitative, or semi-quantitative. Literature review indicates that such types of risk assessment approaches are widely used in the railway safety risk management (Railway Safety, 2002; Muttram, 2002; MR 2005).

2.3.4.1. Quantitative risk assessments

Quantitative risk assessment uses numerical values for both consequences and likelihood by reviewing risk data and information from a variety of sources, such as past accidental records, statistics and databases. The quality of the analysis depends on the accuracy and completeness of the numerical values and the validity of the models used. The aim of quantitative risk assessment is to provide design engineers and safety managers with the quantified occurrence probability of each serious failure condition and the possible consequences, so that potential risks associated with a railway system can be understood (AS/NZS, 1999).

FTA and ETA are two commonly used quantitative assessment techniques to study risks associated with a railway system. A SRM (Muttram, 2002) was developed on the basis of these two techniques by Railway Safety and is used to assess the risk of major hazards in railways. It can provide a structured representation of the causes and consequences of potential accidents arising from railway operations and maintenance on the mainline railway.

FTAis a top-down approach to failure analysis, starting with a potential undesirable event (accident) called as a TOP event, and then determining all the ways in which it can happen. The analysis proceeds by determining how the TOP event can be caused by individual or combined lower level failures or events. The causes of the TOP event are "connected" through logic gates, i.e. AND-gates and OR-gates. An example of a fault tree is shown in Figure 2-4. (Muttram, 2002)

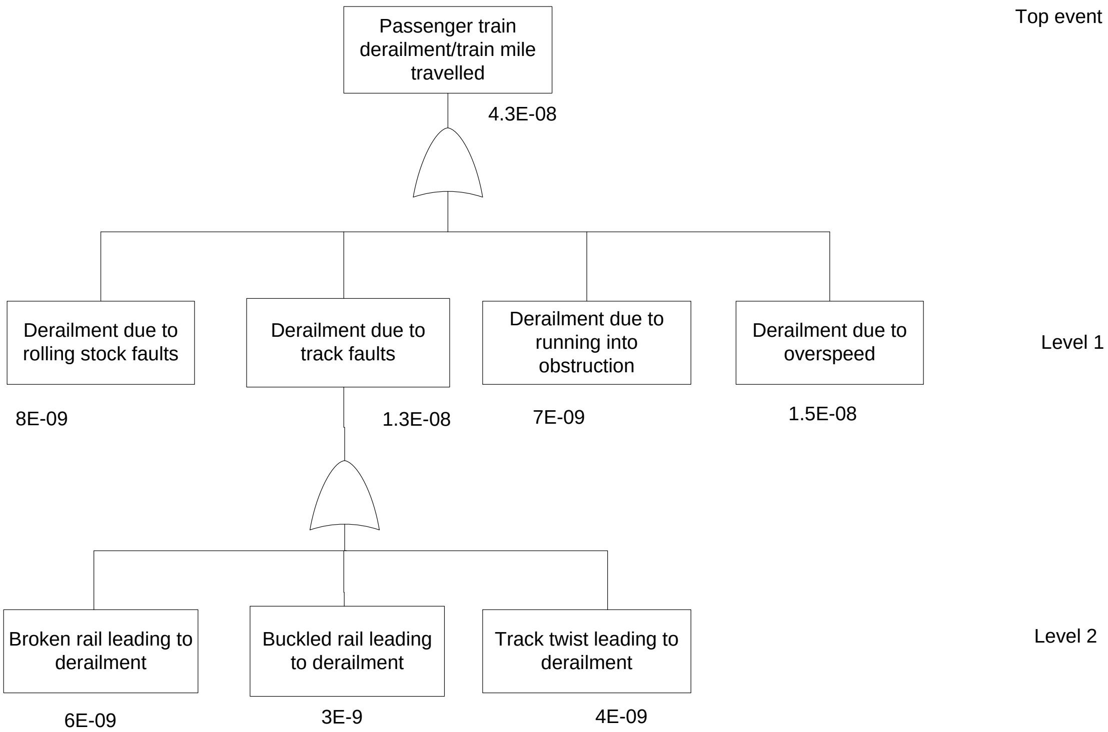


Figure 2-4 An example of a fault tree (Muttram, 2002)

The top event of the fault tree in Figure 2-4 is identified as "Passenger train derailment". It is linked by an OR gate with four basic events at level 1 i.e. "Derailment due to rolling stock faults", "Derailment due to track faults", "Derailment due to running into obstructions" and "Derailment due to over-speeding". This means that the top event happens if any one of these basic occurs at level 1. Another three events at level 2 can also be identified as "Broken rail leading to derailment", "Buckled rail leading to derailment", and "Track twist leading to derailment" which are also connected with "Derailment due to track faults" through an OR gate. In other words, the failure likelihood of "Derailment due to track faults" is the sum of these three events. The failure likelihood of the top event is the sum of the four events at level 1.

FTA can identify all the possible causes of a specified undesired event (TOP event), and lead to improve understanding of system characteristics. Design flaws and insufficient operational and maintenance procedures may be revealed and corrected during the fault tree construction. However, FTA is not suitable for modelling when the available data are of poor quality (AS/NZS 4360, 2004).

ETA is often the partner of fault tree analysis. It is an inductive procedure that shows all possible outcomes resulting from an accidental (initiating) event, taking into account whether installed safety barriers are functioning or not, and additional events and factors (AS/NZS, 1999). By studying all relevant accidental events, the ETA can be used to identify all potential accident scenarios and sequences in a complex system. Design and procedural weaknesses can be identified, and probabilities of the various outcomes from an accidental event can be determined. An example of an event tree is shown Figure 2-5:

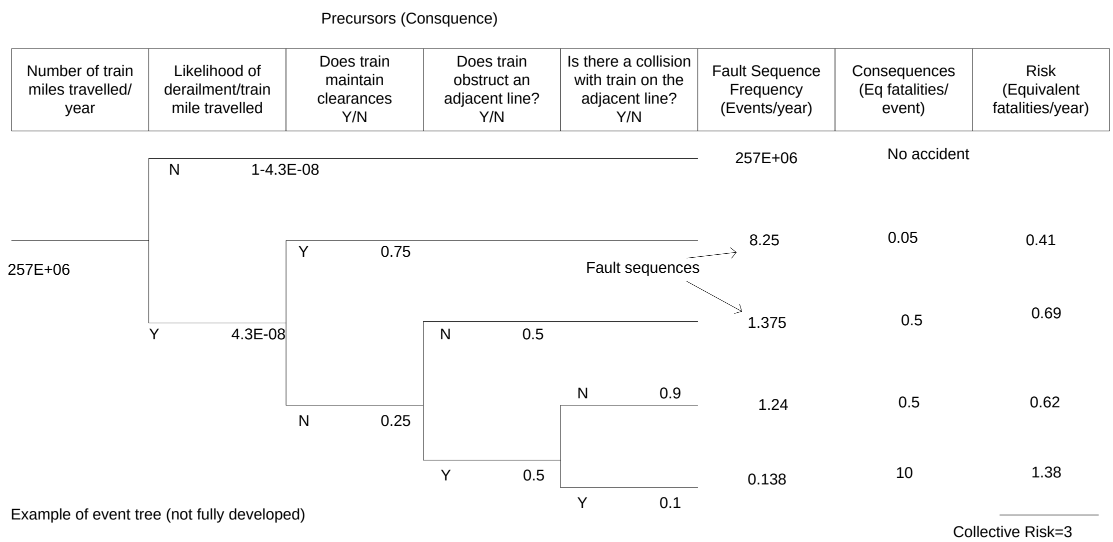


Figure 2-5 An example of event tree (Muttram, 2002)

The example demonstrates how an event tree is used to evaluate the consequences of train derailment. Suppose that train miles travelled are 257E+06 miles per year. There are two branches (i.e. "Yes (Y), derailment" and "No (N), non-derailment") for each decision junction for the probability of derailment. FTA is often applied to estimate the likelihood of the initiating event. In this case, 4.3E-08 is the likelihood of a derailment. Thus, the likelihood of non-derailment is “1-4.3E-08” and no accident train miles travelled is nearly 257E+06 miles per year. Then, according to probability of each branch, the fault sequence frequency through each branch can be calculated. For example, if a derailment occurs and there are no effects on other lines or trains, the fault sequence frequency is 8.25 events per year, which is the product of the number of train miles i.e. 257E+06, the likelihood of derailment i.e. 4.3E-08 and the probability of the branch i.e. 0.75. The consequence of this scenario is 0.5 equivalent fatalities per event, so that the risk of this scenario is 0.69 equivalent fatalities per year, which is the product of frequency and consequences. Then, risk of derailment is calculated as the sum of risk under each scenario, which is 3 equivalent fatalities per year in this case example.

As ETA can visualise event chains following an accidental event, barriers and sequences of activation, it is a good basis for evaluating the need for new/improved procedures and safety functions. However, there is no standard for the graphical representation of the event tree, and only one initiating event can be studied in each analysis. In addition, the analyst must be well trained and experienced to ensure an effective study of a railway system. Furthermore, requirement of data quality is relatively high (HSE 2001).

By using quantitative risk assessment, the potential causes and consequences of a hazard event and characteristics of a system can be identified, assessed and understood. But the quality and validity of the assessment highly rely on the availability, accuracy and completeness of risk data. A full quantitative risk assessment would be extremely time consuming and expensive. (AS/NZS, 1999; AS/NZS 4360, 2004).

2.3.4.2. Qualitative risk assessments

Qualitative risk assessment is a straightforward process. It identifies risk based on the knowledge and judgement of the person who carries out the assessment. Safety risk analysts can use words to describe the magnitude of potential consequences and the likelihood that those consequences will occur. These scales can be adapted or adjusted to suit the circumstances. For example, failure likelihood is usually expressed in a linguistic manner such as “Rare”, “Occasional”, and “Regular”; consequence severity is identified as “Negligible”, “Moderate”, and “Severe”; and risk can be expressed as “Low”, “Medium”, and “High”. Qualitative risk assessment can be fulfilled by various techniques such as interviews, checklists and brainstorming techniques (Thompson and Perry eds., 1992). On the basis of risk assessment results, measures can be taken to eliminate or control hazards.

In practice, Preliminary Hazard Analysis (PHA) (MIL-STD-882D, 1983) and Hazard & Operability (HAZOP) (Kyriakdis, 2003) studies are typical qualitative risk assessment techniques. The HSE has identified a “5-step approach to Risk Assessment” (HSE, 1998) based on PHA to easily conduct qualitative assessment. The five steps are summarised as follows:

1. Identify the hazard.
2. Decide who might be harmed and how.
3. Evaluate the risks and decide on precautions.
4. Record findings and implement them.
5. Review risk assessment and update if necessary.

A risk ranking matrix is normally adopted to evaluate the risks in the assessment, which is also one of the most important qualitative methods and has been widely used in railways, where the failure likelihood (FL) and consequence severity (CS) can be combined in a two-dimensional matrix for risk level allocation based on expert judgements. For example, FL is described as “Rare”, “Occasional” and “Frequent” as shown in Table 2-1. CS is described as “Negligible”, “Moderate”, and “Frequent” as shown in Table 2-2. By combining FL and CS, a risk ranking matrix can be developed as shown in Table 2-3, in which a risk level is described as “Low”, “Medium”, and “High”. Based on Table 2-1 and Table 2-2, the magnitude of the risk of a hazard event can be determined by using the risk ranking matrix. For example, when a hazard event has “Frequent” of FL and “Severe” of CS, the risk level of this event is “High” which can be determined according to the risk ranking matrix.

Index	FL	Meaning
1	Rare	Occurrence is unlikely
2	Occasional	Few occurrences
3	Frequent	Repeated occurrence

Table 2-1 FL categories for qualitative risk ranking matrix

Index	CS	Meaning
1	Negligible	Slight injury no absence from work
2	Moderate	An injury with the potential of absence from work for few days
3	Severe	Serious injury, even single/ multiple fatality

Table 2-2 CS categories for qualitative risk ranking matrix

		CS		
		Negligible	Moderate	Severe
FL	Rare	Low	Low	Medium
	Occasional	Low	Medium	High
	Frequent	Medium	High	High

Table 2-3 Qualitative ranking matrix of FL and CS

Qualitative risk assessment may be used where the numerical data or resources are inadequate for a quantitative analysis. It relies on subjective judgements to assess the risk level of a hazard event, which therefore cannot provide precise results. A semi-quantitative assessment may provide a better understanding of the risks associated with a railway system which is described in the next section.

2.3.4.3. Semi-quantitative risk assessments

In a semi-quantitative risk assessment, qualitative scales such as those described in section 2.3.4.2 are given. The objective is to produce a more expanded ranking scale than is usually achieved in qualitative assessment, not to suggest realistic values for risk such as is attempted in quantitative assessment (AS/NZS, 1999). The value allocated to each description may not be an accurate relationship to the actual magnitude of consequences or likelihood, and those numbers can only be combined using a formula that recognises the limitations of the kinds of scales used (AS/NZS 4360:2004).

Failure modes and effects analysis (FMEA) (SEMATECH, 1992) is a typical semi-quantitative risk assessment technique. The application of this technique aims to identify and analyse all potential failure modes of various parts of a system as well as the effects that these failures may have on the system. The guidance from Railway Safety (2002) describes a method based on FMEA to conduct a semi-quantitative risk assessment within the railway safety case. As described earlier in this thesis, FL and CS are assigned numerical values in accordance with the corresponding categories based on professional judgement as shown in Table 2-4 and Table 2-5. For example, a hazard event with an occurrence of around 31.25 per year is defined as a frequent event. If the hazard event causes around 3.125 equivalent fatalities, the consequence is defined as a severe consequence.

On the basis of the newly defined FL and CS categories, either a numerical risk or risk score of a hazard event can be obtained from the product of its FL and CS numerical values or the summation of its FL and CS ranking indices:

Numerical risk= FL numerical value $\times$ CS numerical value
Risk score= FL ranking index + CS ranking index

For example, a hazard event has a FL of “Frequent”, which is assigned 31.25 failures per year and CS is “Severe” with 3.125 equivalent fatalities with every failure. The numerical risk is 97.66 equivalent fatalities per year, and the risk score is 6. By comparing with the values in the numerical risk matrix of Table 2-6 and risk score matrix of Table 2-7, it can be concluded that the risk level of such a hazard event has a "high" risk level.

Ranking index	FL	Meaning	Approximate numerical value (events/year)
1	Rare	Occurrence is unlikely	0.05
2	Occasional	Few occurrences	1.25
3	Frequent	Repeated occurrence	31.25

Table 2-4 FL categories for semi-quantitative risk assessment

Ranking index	CS	Meaning	Approximate numerical value (equivalent fatalities/event)
1	Negligible	Slight injury no absence from work	0.005
2	Moderate	An injury with the potential of absence from work for few days	0.125
3	Severe	Serious injury, even single/ multiple fatality	3.125

Table 2-5 CS categories for semi-quantitative risk assessment

		CS		
		0.005	**0.125**	**3.125**
FL	**0.05**	2.5E-4	6.25E-3	0.16
	1.25	6.25E-2	0.16	3.91
	31.25	0.16	3.91	97.66

Table 2-6 Numerical risk matrix

		CS		
		1	**2**	**3**
FL	**1**	2	3	4
	2	3	4	5
	3	4	5	6

Table 2-7 Risk score matrix

A semi-quantitative assessment can produce more accurate results of risk rankings than those produced by a qualitative assessment. This approach is widely used in railway risk assessment. Metronet Rail has developed a risk model based on this approach to assess train operations and staff risks (Metronet Rail, 2005). However, care must be taken with the use of semi-quantitative assessment, because the numbers chosen may not properly reflect relativities and this can lead to inconsistent, anomalous or inappropriate outcomes ((AS/NZS 4360:2004).

2.3.4.4. Software developments for railway safety risk assessments

On the basis of risk assessment techniques as described in the above sections, many commercial software have been developed which are summarised in Table 2-8. However, most of software has been developed mainly based on FTA and ETA, also including FMEA and Monte Carlo simulation.

Software	Applied area	Techniques	Website
AgenaRisk	Aerospace, Banking, Defence, Energy, Technology, Telecoms, Transportation	FTA	www.agenarisk.com/
RiskSpectrum	Nuclear power plants	FTA&ETA, FMEA	www.riskspectrum.com/
QRAS	Aerospace, Defence, Health Care, and other industries	FMEA, FTA&ETA	www.itemsoft.com/
SAFETI-PHAST	Onshore, Finance	HAZOP, What if, checklist, PHA, FMEA	www.dnv.com
NEPTUNE	Offshore	ETA , what-if analysis	www.dnv.com
SAFETI-Frequency	Offshore	FTA, ETA, Monte Carlo simulation	www.dnv.com
ASAP	leaks, fires and explosions on oil and gas installations	QRA	www.lilleaker.com/ASAP.asp
LEAK	Calculate leak frequency	QRA	www.dnv.com
FaultTree+	Raliways	FTA, ETA	www.isograph-software.com
LOGAN	No specific area	FTA, ETA, Monte Carlo simulation	www.rmclogan.co.uk
PHA-Pro 6	No specific area	HAZOP, what-if analysis, checklist, PHA, FMEA	www.dyadem.com

Table 2-8 Lists of commercial risk assessment software

The SRM (Safety Risk Model) mentioned in Section 2.3.4.1 is developed on the basis of the FaultTree+ software by Isograph Ltd. It provides improved analysis of the results from FaultTree+ in terms of the overall collective risk from individual or groups of fault tree and event tree analysis models, the risk profiles, and the risk contributions from individual or groups of precursors. Isograph also develops a RiskVu package that interfaces directly link with FaultTree+, which facilitates the use of the software.

The SRM represents a comprehensive system-wide computer based model of the UK mainline railway network. The model allows for (Muttram, 2002):

- risk profiles for all groups of hazardous events to be represented graphically;
- determination of the risk contribution and risk profile, from individual or groups of causes and consequence precursors;
- determination of the frequency and average consequences per event for each hazardous event;
- determination of the relationship between the frequency of occurrence and the number of fatalities for all groups of or individual hazardous events;
- provides the basis for assessing the risk for a particular line or route, or for a particular train operating company.

However, it should be noted that in order to assess the risk for a particular line or route, or for a particular train operating company, each model, each assumption and each data input to the SRM must be examined for relevance to the particular line or route, or for a particular train operating company. Therefore, SRM may have the following pitfalls (Railway safety, 2003):

- time consuming;
- analysis could be diverted into endless discussions of details;
- experts' judgement is represented by a single number;
- no standard for the graphical representation of the event tree;
- only one initiating event can be studied in each analysis;
- not well suited for handling common cause failures in the quantitative analyses.

2.3.5 Discussions

A risk assessment can be undertaken on a quantitative or a qualitative, or a semi-quantitative basis depending on the complexity of the problem, the objectives of the assessment, and availability of information, data and resources. When detailed risk analysis is required, a quantitative risk assessment approach may be the best choice, but it is complicated and time consuming. If data is of poor quality, it becomes impossible to carry out a quantitative risk assessment. Applications of qualitative risk assessment would then be necessary. However, the results from qualitative risk assessments are quite general, and may be only suitable for initial risk screening activities. A semi-quantitative assessment can produce a more expanded raking scale than those in a qualitative assessment, but it only delivers limited information due to the limitation of input data (Chen et al., 2007 &2011).

In railways, risk assessment is a very complicated subject as the overall system is very complex, and its risk is determined by numerous factors. Quantitative risk assessment approaches such as FTA and ETA are currently used in railway safety risk analysis. They can provide relevant detailed results, but they are often not effective to handle with the uncertainty of information as they rely heavily on supporting statistical information which may not be available. In the safety risk assessment, collecting sufficient data based on statistical probability of failure is a costly and difficult undertaking, and the relevance of data to any particular system, as well as its validity, is often questionable. Furthermore, in many situations, the item of the probability of failure is needed but it does not exist, therefore it must be estimated based on engineering judgement or experience from similar items. Quantitative risk assessment may not be suitable for such a situation, while qualitative or semi-quantitative assessment may not solve the problem efficiently, as a single number or word may not include all the necessary information (Chen et al., 2007 &2011).

A fuzzy reasoning approach may be more appropriate in the situations where there is a high level of uncertainty within the risk data. It allows imprecision or approximated information in its analysis process, which helps to restore integrity to safety risk analysis. It also possesses the ability to mimic the human mind to effectively employ approximate reasoning that enables risk analysts to specify mapping rules in terms of words rather than numbers, and approximate function rather than exact reasoning. It has been shown that fuzzy reasoning can model non-linear functions of arbitrary complexity to a desired degree of accuracy (An et al., 2007; Chen et al., 2007 & 2011). The proposed railway safety risk model in this study will address these issues.

2.4 Summary

The chapter reviews the potential problems related to railway safety and common types of railway accidents. In order to eliminate risks and improve railway safety, railway safety risk assessment must be undertaken. This chapter then also reviews current railway safety risk assessment approaches including the top-down approach, the bottom-up approach and quantitative, qualitative and semi-quantitative risk analysis techniques. Most of commercial software currently used in railway safety risk analysis have also been reviewed. The benefits and pitfalls are addressed. The review ends with a conclusion that current railway safety risk assessment techniques may not suitable for circumstances where a high level of uncertainty is involved in the safety risk data or the required information is not available. A fuzzy reasoning approach may be more appropriate to solve such problems.

CHAPTER 3: FUNDAMENTALS OF FRA AND MODIFIED FUZZY-AHP

3.1 Introduction

The proposed safety risk model is developed by using fuzzy reasoning approach (FRA) combined with a Modified fuzzy analytical hierarchy process (Fuzzy-AHP). This chapter introduces the concepts of fuzzy set and fuzzy number and describes the fundamentals of FRA and modified Fuzzy-AHP.

3.2 Fuzzy Expression

Fuzzy theory and the possibility theory were firstly introduced by Zadeh (1965 & 1978), which have been widely used to deal with uncertainties in the measurement of risks in the fields of such as finance, business, system control, risk assessment and the environment. In these applications, the concepts of fuzzy set and fuzzy number have been frequently applied. A fuzzy set is an extension of a classical set (Zadeh 1965; Bojadziev and Bojacziev 1997). Instead of using a binary membership function in a classical set, which only tells whether an object belongs to the set or not, fuzzy set applies a continuous graded membership function which also indicates how much the object is close to the set. A fuzzy number is a parametric representation of a convex and normalized fuzzy set.

3.2.1 Fuzzy set

A fuzzy set $\tilde{A}$ on a universe of discourse U characterised by a membership function (MF) $\mu_{\tilde{A}}(x)$ is defined as (Zadeh, 1965):

$$\tilde{A} = \left\{ \left(x, \mu_{\tilde{A}}(x) \right) \middle| x \in U, \mu_{\tilde{A}}(x) \in [0,1] \right\}. \qquad \text{Eq. 3-1}$$

If $\max\left(\mu_{\tilde{A}}(x)\right)=1$, the fuzzy set $\tilde{A}$ is called *normalized*; otherwise the set is called *nonnormalized*. If the number of solutions to equation $\mu_{\tilde{A}}(x)=\alpha$ is less than three for all α in the interval $(0,1]$, the fuzzy set $\tilde{A}$ is called *convex*; otherwise is called *nonconvex*.

The basic operations on fuzzy sets are *equality*, *inclusion*, *proper subset*, *complementation*, *intersection*, and *union*, in which, *intersection*, and *union* are most commonly used fuzzy set operators in safety risk analysis, and they are also called *AND* and *OR* operations respectively. Consider two fuzzy sets $\tilde{B}$ and $\tilde{C}$,

$$\tilde{B}=\left\{\left(x,\mu_{\tilde{B}}(x)\right)\middle|x\in U,\mu_{\tilde{B}}(x)\in[0,1]\right\},$$

$$\tilde{C}=\left\{\left(x,\mu_{\tilde{C}}(x)\right)\middle|x\in U,\mu_{\tilde{C}}(x)\in[0,1]\right\}.$$

The operations with $\tilde{B}$ and $\tilde{C}$ are introduced via operations on their membership function $\mu_{\tilde{B}}(x)$ and $\mu_{\tilde{C}}(x)$ (Bojadziev and Bojacziev 1997). The operation *intersection* of $\tilde{B}$ and $\tilde{C}$ is denoted as $\tilde{B}\cup\tilde{C}$, whose MF is defined as:

$$\mu_{\tilde{B}\cup\tilde{C}}(x)=\min\left(\mu_{\tilde{B}}(x),\mu_{\tilde{C}}(x)\right) \qquad \text{Eq. 3-2}$$

The operation *union* of $\tilde{B}$ and $\tilde{C}$ is denoted as $\tilde{B}\cup\tilde{C}$, whose MF is defined as:

$$\mu_{\tilde{B}\cap\tilde{C}}(x)=\max\left(\mu_{\tilde{B}}(x),\mu_{\tilde{C}}(x)\right) \qquad \text{Eq. 3-3}$$

3.2.2 Fuzzy number

A fuzzy number is defined in the universe R as a *convex* and *normalized* fuzzy set (Bojadziev and Bojacziev 1997), and it is a parametric representation of the fuzzy set. There are various fuzzy numbers available such as triangular fuzzy number, trapezoidal fuzzy number, bell-shaped fuzzy number, and etc. However, triangular and trapezoidal fuzzy numbers are the most widely used in the engineering risk analysis because of their intuitive appeal and perceived computational efficacy (Giachetti et al. 1997).

A trapezoidal fuzzy number can be defined as $A=\left(a,b,c,d\right)$, and the MF of its corresponding fuzzy set $\tilde{A}$ is defined as:

$$\mu_A(x)=\begin{cases}(x-a)/(b-a), & x\in[a,b],\\ 1 & x\in[b,c]\\ (x-d)/(c-d), & x\in[c,d],\\ 0, & otherwise.\end{cases} \qquad \text{Eq. 3-4}$$

where four real numbers (*a*, *b*, *c*, and *d* are also vertex values of a trapezoidal membership function) with satisfaction of the relationship $a\le b\le c\le d$ determine the x coordinates of the four corners of a trapezoidal membership function as shown in Fig. 3-1(A) . If $b=c$, the fuzzy number becomes a triangular fuzzy number as shown in Fig. 3-1(B), which could be deemed to be special format of a trapezoidal fuzzy number. A non-fuzzy number A can then be expressed as $\left(a,a,a,a\right)$. By the extension principle of fuzzy set (Dubois and Prade 1980; Chen 1998; Chen et al 2006; Gu and Zhu, 2006), the fuzzy operations for trapezoidal fuzzy numbers have been developed and applied. The fuzzy addition $\oplus$ of any two trapezoidal fuzzy numbers are also trapezoidal fuzzy numbers while fuzzy multiplication $\otimes$, fuzzy division $\varnothing$ and fuzzy exponent of any two trapezoidal fuzzy numbers may be either trapezoidal fuzzy numbers or other types of fuzzy numbers. For example, given any two positive trapezoidal fuzzy numbers, $B=(a_B,b_B,c_B,d_B)$ and $C=\left(a_C,b_C,c_C,d_C\right)$, some commonly used operations of these fuzzy numbers can be expressed as follows:

$$B \oplus C = (a_B + a_C, b_B + b_C, c_B + c_C, d_B + d_C)$$ Eq. 3-5

$$B \otimes C \cong (a_B \times a_C, b_B \times b_C, c_B \times c_C, d_B \times d_C)$$ Eq. 3-6

$$B \varnothing C \cong (a_B / d_C, b_B / c_C, c_B / b_C, d_B / a_C)$$ Eq. 3-7

$$B^k \cong ((a_B)^k, (b_B)^k, (c_B)^k, (d_B)^k),\ \ k>0\,.$$ Eq. 3-8

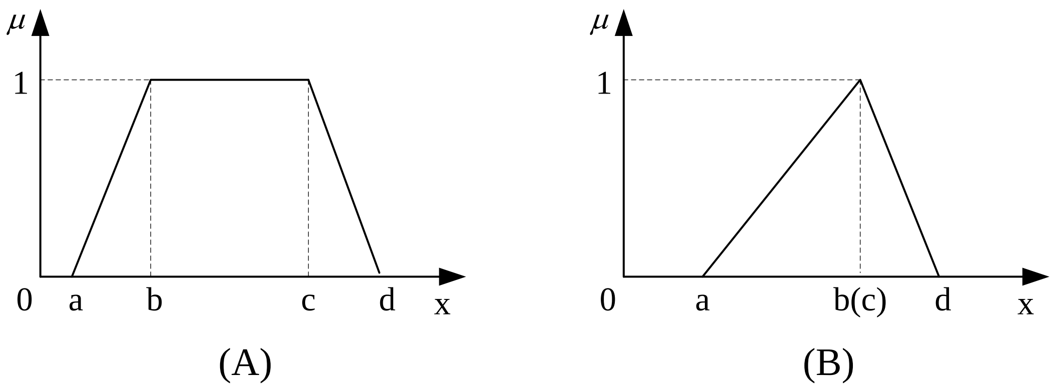


Fig. 3-1 Trapezoidal and triangular fuzzy numbers and corresponding MFs

3.3 Fundamental of FRA

Fuzzy reasoning approach (FRA) has been developed based on the concept of fuzzy sets and inference mechanism, which generalises an ordinary mapping of a function to a mapping between fuzzy sets (Lee, 2005, An et al., 2000a and b). The inference mechanism is based on the compositional rule of inference and the result is derived from a set of fuzzy rules and given inputs. It indicates that FRA possesses the ability to model a complex non-linear function to a desired degree of accuracy. Therefore, FRA has been widely applied to risk assessment, data classification and system control. In this section, basic terms of linguistic variables, fuzzy rulebase and fuzzy inference process are presented, which are essential knowledge for developing a FRA safety risk model.

3.3.1 Linguistic variables

Linguistic variables are the generalisation of ordinary variables, whose values are words or sentences in natural or artificial languages rather than real numbers. They are defined by the following quintuple (Lee, 2005):

Linguistic variable = $\left(x, T\left(x\right), U, M\right)$

where

x : name of variable

$T\left(x\right)$: set of linguistic terms which can be a value of the variable

U : set of universe of discourse which defines the characteristics of the variable

M : semantic rules which map terms in $T\left(x\right)$ to fuzzy sets in U

For example, consider a linguistic variable X to describe age approximately, whose name is “AGE” as shown in Fig. 3-2. Where

$X = (AGE, T(AGE), U, M)$

AGE : name of the variable X

$T\left(AGE\right)$: {very young, young, middle age, old} set of linguistic terms in the discussion of age.

U : $\left[0,100\right]$ universe of discourse

By using Eq 3-1,

$$M(young) = \{(x, \mu_{young}(x)) | x \in U\}$$

$$\mu_{young}(x) = \begin{cases} (x-5)/15 & x \in [5,20], \\ 1 & x \in [20,30], \\ (45-x)/15 & x \in [30,45], \\ 0 & otherwise. \end{cases}$$

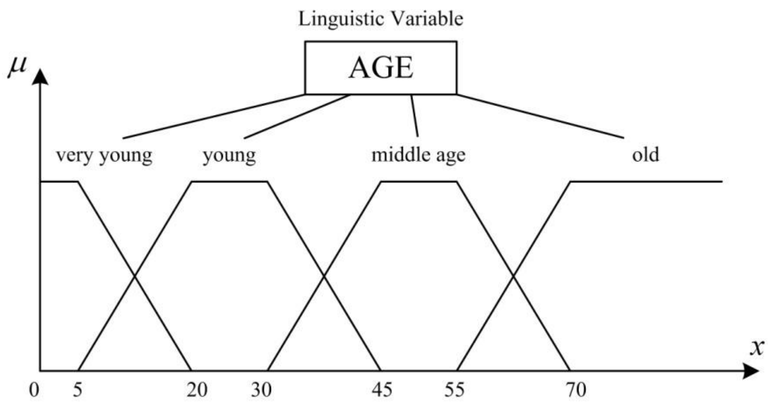


Fig. 3-2 Linguistic terms of the linguistic variable AGE

3.3.2 Fuzzy rulebase

A major component of a FRA model is fuzzy rulebase, which consists of a set of fuzzy rules, and these rules are expressed in the form of IF-THEN statements. For example, the following is a fuzzy IF-THEN rule:

$$\text{IF } x \text{ is } A \text{ AND } y \text{ is } B, \text{ THEN } z \text{ is } C$$

Where A, B and C are linguistic terms, "IF x is A AND y is B" is called the "*antecedent (IF part)*" of the rule and "THEN z is C" is called "*consequent (THEN part)*". If there are more than one arguments in the IF part, then AND or OR operation needs to be applied.

Because a multi-output system can always be decomposed into a collection of a single-output system, therefore, only the multi-input-single-output system is presented (Lee, 2005, An et al, 2000a &b; Yao et al, 2006). For example, the *i*th fuzzy IF-THEN rule in the fuzzy rule base is defined as:

$$R_i\text{: IF } X_1 \text{ is } A_1^i \text{ and} \ldots \text{ and } X_n \text{ is } A_n^i \text{ , THEN } Y \text{ is } B^i \qquad \text{Eq. 3-9}$$

where $X_1, X_2, ..., X_n$ and Y are linguistic variables, and $A_1^i, A_2^i \ldots A_n^i$ and B^i are linguistic terms in the *i*th rule, and they belong to the above linguistic variables, respectively. In order to build a robust fuzzy rulebase, three major properties of fuzzy rules must be taken into consideration, which are outlined as follows (Wang, 1997; Sii et al., 2001; An et al., 2000a & b; An et al., 2006 & 2007):

(1) Completeness: a set of fuzzy IF-THEN rules is complete if for any input values, there is at least one rule in the fuzzy rule base. In other words, the completeness of a set of rules means that at any point in the input space there is at least one rule that 'fires', which means the membership value of the IF part of the rule at this point is non-zero.

(2) Consistency: a set of fuzzy IF-THEN rules is consistent if there are no rules with the same IF part, but different THEN parts.

(3) Continuity: a set of fuzzy IF-THEN rules is continuous if there do not exist such neighbouring rules whose THEN part fuzzy sets have empty intersection, i.e. they do not intersect.

3.3.3 Fuzzy inference process

A fuzzy IF-THEN rulebase is the core of the fuzzy inference process for formulating the mapping from given input fuzzy sets to an output fuzzy set. Once the rulebase is established, fuzzy inference process can be carried out as shown in Fig. 3-3. Fuzzy set inputs are directly input into the fuzzy inference system to determine which rules are relevant to the current situation, and the results from inference of individual rules are then aggregated to the output result from inference with current inputs. The overall process is developed on the basis of the Mamdani method (Lee, 2005; An et al., 2006 & 2007).

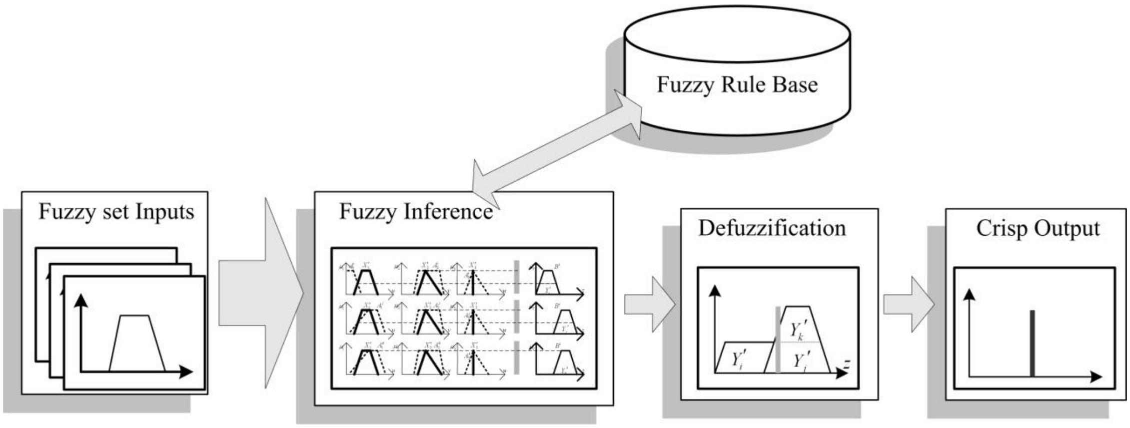


Fig. 3-3 Fuzzy inference process

Supposing there are m rules in the rulebase, and the ith rule is defined as:

$$R_i\text{: IF } X_1 \text{ is } A_1^i \text{ and} \ldots \text{and } X_j \text{ is } A_j^i \text{ and} \ldots \text{ and } X_n \text{ is } A_n^i \text{ , THEN } Y \text{ is } B^i. \qquad \text{Eq. 3-10}$$

where there are n arguments in the IF part connected with the AND operation, and $X_1, X_2, \ldots, X_n$ and Y are linguistic variables in their corresponding universe discourse, and $A_1^i, A_2^i \ldots A_n^i$ and B^i are linguistic terms of linguistic variables $X_1, X_2, \ldots, X_n$ and Y. The calculation of the fire strength α_i of rule R_i with input fuzzy sets $\tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_n$ using fuzzy intersection operation is given by:

$$\alpha_i = \min\left[\max\left(\mu_{X_1}(x_1) \wedge \mu_{A_1^i}(x_1)\right), \max\left(\mu_{X_2}(x_2) \wedge \mu_{A_2^i}(x_2)\right), \ldots, \max\left(\mu_{X_n}(x_n) \wedge \mu_{A_n^i}(x_n)\right)\right]$$

Eq. 3-11

Where $\mu_{X_1}(x_1), \mu_{X_2}(x_2), \ldots, \mu_{X_n}(x_n)$ are the MFs of fuzzy sets $\tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_n$, respectively, and $\mu_{A_1}(x_1), \mu_{A_2}(x_2), \ldots, \mu_{A_n}(x_n)$ are the MFs of fuzzy sets of linguistic terms $A_1^i, A_2^i, \ldots, A_n^i$ in rule R_i. After the fuzzy implication, the truncated MF μ'_{B^i} of the inferred conclusion fuzzy set of rule R_i can be obtained by:

$$\mu'_{B^i}(y) = \alpha_i \wedge \mu_{B^i}(y) \qquad \text{Eq. 3-12}$$

Where α_i is the fire strength of rule R_i, and $\mu_{B^i}(y)$ is the MF of linguistic term $\tilde{B}^i$ and y is an input variable in the universe of discourse.

The firing strength is implicated with the value of the conclusion MF and the output is a truncated MF. The truncated MF's corresponding fuzzy sets that represent the implication output fuzzy sets of rules are aggregated into a single fuzzy set. The MF $\mu'_B(y)$ of output fuzzy set after aggregation using fuzzy union (maximum) operation is denoted by:

$$\mu'_B(y) = \bigvee_{i=1}^{n} \mu'_{B^i}(y) \qquad \text{Eq. 3-13}$$

where μ'_{B^i} is the MF of conclusion fuzzy set of rule R_i and n is the total number of rules in the rule base.

As the output from the fuzzy inference system is a fuzzy set, defuzzification needs to be applied to convert the fuzzy result into a matching numerical value. The centre of area method (Lee, 2005; An et al., 2006 & 2007) is employed for defuzzification. Assume the output fuzzy set obtained from the fuzzy inference system is $\tilde{B}' = \{(y, \mu'_B(y)) \mid y \in Y, \mu'_B(y) \in [0,1]\}$, the matching crisp value c from the MF of

$\mu'_B(y)$ of the conclusion fuzzy set can be calculated by:

$$c = \frac{\sum_{j=1}^{m} \mu'_B(y_j) \cdot y_j}{\sum_{j=1}^{m} \mu'_B(y_j)} \qquad \text{Eq. 3-14}$$

where *m* is the number of quantisation levels of the conclusion fuzzy set.

Fig. 3-4 demonstrates the fuzzy inference process with three input fuzzy sets: trapezoidal fuzzy set X'_1, triangular fuzzy set X'_2 and crisp set X'_3. These inputs are fired with Rules R_i and R_j, where Rule R_j is fired twice as fuzzy sets X'_1 and A_1^j have two intersection points. The fuzzy sets Y'_i, Y'_j, and Y'_k derived from implication are determined by *Minimum* operation, and then they are aggregated together by *Maximum* operation. Finally, the output from the defuzzification is calculated by the centre of area method as described above.

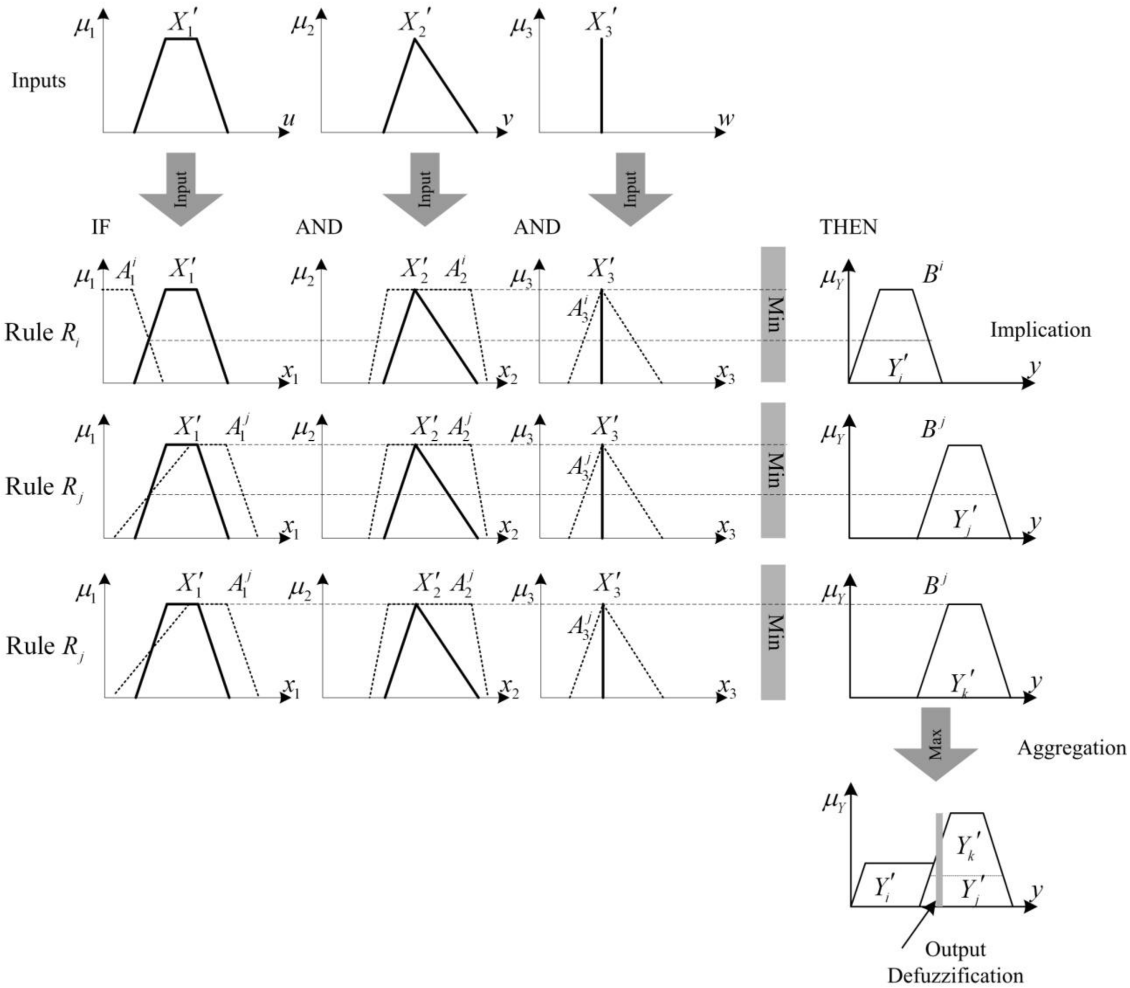


Fig. 3-4 Fuzzy inference process with three input fuzzy sets

FRA is capable to deal with qualitative information so that imprecision or approximate information can be taken into consideration in the risk assessment. It also provides a framework that transforms a human knowledge base into a non-linear mapping. Because the risk contributions of components and subsystems to a system are different, the weight factor (WF) of each component or subsystem within the system should be considered in order to calculate their relative contributions to the RL of the system. Thus, an improved fuzzy analytical hierarchy process technique has been developed and incorporated into the proposed risk model in this study to use its advantages in determining the relative importance of components and subsystems. Therefore, the risk assessment can be progressed from component level to the subsystem level and finally to the system level. Such a technique will be introduced in the following section.

3.4 Fundamental of Fuzzy-AHP

Many methods can be used to determine the weight factors, such as the Weight Sum Model (WSM) (Fishburn, 1967), Weighted Product Model (WPM) (Miller and Starr 1969), Simple Multiattribue Rating Technique (SMART) (Winterfeldt and Edwards, 1986) and Analytical Hierarchy Process (AHP) (Satty, 1980). However, compared with other methods, AHP has its advantages in determining weight factors both in single and multi-dimensional decision making, and has been integrated with risk assessment techniques (Satty, 1980; Vaidya and Kumar, 2006).

AHP is introduced by Satty in 1980. Since then, it has been widely used in multiple criteria decision-making. It decomposes a complex problem into a hierarchy, in which each level is composed of specific elements. Pairwise comparisons for each level in the hierarchy need to be carried out in order to obtain the weight factor (WF) of each element at that level with respect to one element at a higher level. AHP enables decision makers to analyse a complex problem in a hierarchy with quantitative and qualitative data and information in a systematic manner. It also attempts to resolve conflicts and analyse judgments whilst determining the relative importance of a set of certain criteria. Many outstanding works have been published based on AHP, including the applications of AHP in different fields such as planning, selecting a best alternative, resource allocations, resolving conflict, optimisation, and etc. (Zahedi, 1986; Vargas, 1990; Vaidya and Kumar, 2006). However, some deficiencies have been found when applying AHP in practice (Laarhoven and Pedrycz, 1983; Buckley, 1985; Yu 2002; Mikhailov 2004). For example, because the AHP only provides a crisp scale set, participating decision makers have to determine a definite number within the scale set. Therefore, it is difficult to handle the uncertainty in converting experts' imprecise subjective judgments to crisp numbers. Thus, sometimes, it is difficult for experts to express their judgments if they are not confident in relative importance between two alternatives. The applications of Fuzzy analytic hierarchy process (Fuzzy-AHP) may therefore solve such a problem, which is described in section 3.4.1.

3.4.1 Fuzzy-AHP process

As stated earlier in section 3.4, the AHP cannot deal with the fuzziness during decision making. Laarhoven and Pedrycz (1983) have extended Saaty's AHP into Fuzzy-AHP by introducing a triangular fuzzy number into the pairwise comparison matrix of AHP. After that, Buckley(1985) introduced the trapezoidal fuzzy number into Fuzzy-AHP. The purpose of these developments is to solve vague problems during the decision making process. Thus, the application of Fuzzy-AHP not only inherits the advantages of the traditional AHP but also possesses the ability to deal with uncertainty. It is more flexible for experts to express their judgments in either linguistic terms or exact numbers when determining the relevant importance of alternatives (Cheng et al., 1999; Bozdag, 2003; Wu et al., 2004; Kahraman, 2004), especially in risk assessment (Murtaza, 2003; Huang et al., 2006; An et al., 2007; Chen et al., 2007).

A Fuzzy-AHP approach can be simplified as a process of calculating weight factors of alternatives at a level in a hierarchy or of a certain criterion. The process is described as follows:

Step 1: Establishment of a Fuzzy-AHP estimation scheme

Fuzzy-AHP determines weight factors (WFs) by conducting a pairwise comparison. The comparison is based on an estimation scheme of intensity of importance using linguistic terms. Each linguistic term has a corresponding fuzzy number as shown in Table 3-1. Linguistic terms 1 to 9 describe the intensities of preference varying from *equal importance* to *absolute importance*, and linguistic terms 2, 4, 6 and 8 are the intermediate descriptors between them.

Index	Linguistic terms	Fuzzy numbers
1	Equal importance	(1,1,1,2)
2	Between equal and weak importance	(1,2,2,3)
3	Weak importance	(2,3,3,4)
4	Between weak and strong importance	(3,4,4,5)
5	Strong importance	(4,5,5,6)
6	Between strong and very strong importance	(5,6,6,7)
7	Very strong importance	(6,7,7,8)
8	Between very strong and absolute importance	(7,8,8,9)
9	Absolute importance	(8,9,9,9)

Table 3-1 Comparison scheme

Step 2: Construction of fuzzy comparison matrix M

The pairwise comparison matrix M can be developed on the basis of Table 3-1 as described in Step 1. Each element of matrix M presents the preference intensity of one event over another. The fuzzy comparison matrix M is defined as:

$$M = \begin{pmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,n} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,n} \\ \vdots & \vdots & m_{i,j} & \vdots \\ m_{n,1} & m_{n,2} & \cdots & m_{n,n} \end{pmatrix} \quad \text{Eq. 3-15}$$

$$m_{j,i} = 1/m_{i,j} = \{1/a_{i,j}, 1/b_{i,j}, 1/c_{i,j}, 1/d_{i,j}\} \quad \text{Eq. 3-16}$$

where $a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j}$ >1 stands for the *i*th event is relatively more important than the *j*th event, $a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j}$ =1 stands for the *i*th and *j*th events are equally important and $a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j}$ <1 stands for the *i*th event is relatively less important than the *j*th event.

Step 3: Calculation of Fuzzy weights

The fuzzy WF of each event can be calculated (Buckley, 1985) based on Eqs. 3-5 and 3-8:

$$\begin{aligned} u_i &= (m_{i,1} \otimes m_{i,2} \otimes \cdots \otimes m_{i,j} \otimes \ldots \otimes m_{i,n})^{1/n} \\ w_i &= \frac{u_i}{u_1 \oplus u_2 \oplus \cdots \oplus u_i \oplus \cdots \oplus u_n} \end{aligned} \quad , \ \forall i = 1,2,\cdots,n \qquad \text{Eq. 3-17}$$

where $m_{i,j}$ is the fuzzy preference value of the *i*th event over the *j*th event, and u_i is the geometric mean of the fuzzy preference value of the *i*th event over each other event, and w_i is the fuzzy WF of the *i*th event.

Step 4: Defuzzification and normalisation

As the fuzzy WFs are presented in terms of fuzzy numbers, it is necessary to convert fuzzy numbers into crisp values (Bojadziev and Bojacziev 1997). The fuzzy WF w_i of the *i*th event is defined

$$w_i' = \frac{a_i + 2(b_i + c_i) + d_i}{6} \qquad \text{Eq. 3-18}$$

Then, normalised WF w_i'' of the *i*th event can be calculated by

$$w_i'' = \frac{w_i'}{\sum_{i=1}^{n} w_i'} \qquad \text{Eq. 3-19}$$

It can be seen that $n(n-1)/2$ judgements in a traditional fuzzy-AHP process are needed in order to establish a comparison matrix with n events. However, there is a lack of consistency test in such a process. Moreover, with the numbers of events increasing, the numbers of comparisons are increased rapidly. Therefore, the fuzzy multiplicative consistency method may be needed.

3.4.2 Modified Fuzzy-AHP process

The application of Fuzzy-AHP in a risk analysis is to determine the fuzzy priorities by conducting a pairwise comparison from a group of risk analysts. However, the risk analysts often face the circumstances where huge pairwise comparison matrices have to be completed. Even if it is a single pairwise comparison matrix, it still requires $n(n-1)/2$ judgements at a level with n alternatives. Therefore, with the numbers of alternatives increasing, the numbers of comparisons are increased rapidly. As a result, the judgements will mostly become inconsistent. Thus, consistency tests are required to avoid misleading solutions. If a comparison matrix fails the consistency test, the risk analysts must re-do the judgements until a reliable matrix can be obtained. Because the judgements are crisp values and the judgements in Fuzzy-AHP method are given by fuzzy numbers, the likelihood of having inconsistent crisp numbers within the given fuzzy numbers is therefore far greater. Furthermore, because risk analysts are required to provide the comparison judgements using fuzzy numbers, this also involves huge work and the comparison may be highly unrealistic. Therefore, methods have been developed in the literature to use consistency tests to avoid inconsistency in risk analysis (Leung and Cao, 2000; Huang et al., 2005&2006; An et al., 2007; Chen et al., 2007). These methods of determination of the consistency of a fuzzy positive reciprocal matrix can be used in risk analysis; however, these proposed methods will become very complex with the numbers of alternatives increasing.

Preference relation method is a useful method that the most common representation of information used for solving decision making problems due to their effectiveness in modelling decision processes (Wang and Chen, 2008). In the process of decision making, risk analysts generally need to compare a set of decision alternatives with respect to a single criterion, and construct preference relations. In general, the preference relation takes the form of multiplicative preference relations or fuzzy preference relations, whose elements estimate the dominance of one alternative over another by using linguistic variables rather than numerical ones (Satty, 1980; Herrera et al., 2001; Fan et al., 2006; Wang and Fan, 2007; Berredo, 2005; Ekel, 2006; Xu, 2004).

In a preference relation, a risk analyst associates to every pair of alternatives a value which presents the degree of preference of the front alternative over the one behind (Satty, 1980; Berredo, 2005; Ekel, 2006; Herrera et al., 2001; Fan et al., 2006; Wang and Fan, 2007). For example, by studying the properties of consistent preference relations, Herrera-Viedma et al (2004) proposed a new concept of consistency based on additive transitivity property of fuzzy preference relations to avoid misleading conclusions. Based on this characterisation, this study proposed a method for constructing consistent comparison matrices from a set of n-1 preference data, which allows a large amount of required judgements taken from the risk analysts to be reduced, and the consistency of comparison matrices based on the preferences transformed from the judgements can be guaranteed.

Wang and Chen (2008) proposed a method using triangular fuzzy numbers to construct a fuzzy comparison matrix based on consistent fuzzy preference relations in order to enhance the consistency of the fuzzy-AHP method and also to reduce the amount of risk analysts judgements. In this method, the comparison matrix is established by using the additive transitivity property and consistency so that only n-1 comparison judgements are required at a level with n alternatives. However, this method cannot be directly used for construction of the comparison matrices on the basis of multiplicative preference relations without transforming multiplicative preference relations into fuzzy preference relations. The applications of fuzzy-AHP in risk information analysis have proved that the use of multiplicative preference relations is more effective and efficient (Huang et al. 2005; Huang et al. 2006; An et al. 2007; Chen et al. 2007). The following section presents a new method of application of fuzzy multiplicative consistency method to improve the consistency of fuzzy-AHP on the basis of multiplicative preference relations (Buckley, 1985) with trapezoidal fuzzy numbers in the risk assessment process. The principle and algorithm of the proposed method are also discussed. The new method can improve the consistency of the comparison matrices to avoid misleading conclusions. It will ensure the consistency of judgements and provide more reliable results.

3.4.2.1. Multiplicative preference relations

For a set of alternatives at a particular level of a hierarchical structure, multiplicative preference relations provide risk analysts with values presenting varying degrees of preference for the front alternative over the one behind. Suppose that a set of events is $A = \{A_1, A_{2,} \cdots, A_n\}$ and $n \geq 2$, for which a pairwise comparison needs to be conducted. Preference relation is expressed in multiplicative preference relation format *M*. The definition and proposition (Herrera-Viedma et al. 2004) are summarised as follows.

A multiplicative preference relation M in a set of events A is presented by a matrix $M \subset A \times A, M = (m_{i,j})$, where $m_{i,j}$ is interpreted as the preference intensity of two events A_i and A_j, i.e., A_i is $m_{i,j}$ times as important as A_j. The measurement of $m_{i,j}$ uses a ratio scale defined between 1 and 9 (Satty, 1980), where $m_{i,j} = 1$ indicates the absence of a difference between A_i and A_j, and $m_{i,j}$ =9 represents that A_i is absolutely more important than A_j. In this case, the preference relation matrix M is usually assumed to be a multiplicative reciprocal, i.e. $m_{i,j} \times m_{j,i} = 1$, $i, j \in \{1,2,...,n\}$.

Definition: A reciprocal multiplicative preference relation $M = (m_{i,j})$ is consistent if $m_{i,j} \times m_{j,k} = m_{i,k}$, $i, j, k \in \{1,2,...,n\}$ and $i \leq j \leq k$.

In other words, if a comparison matrix *M* is consistency, it has to satisfy

$m_{i,j} \times m_{j,k} = m_{i,k}$. Thereby, Herrera-Viedma et al (2004) proposed a method to construct consistent multiplicative preference relations from a set of $n-1$ preference intensities, and developed important propositions.

Proposition 1: A multiplicative preference relation $M = (m_{i,j})$ is consistent if and only if $m_{i,j} \times m_{j,k} = m_{i,k}, i \le j \le k$.

Proposition 2: For a reciprocal multiplicative preference relation $M = (m_{i,j})$, the following statements are equivalent:

$$m_{i,j} \times m_{j,k} = m_{i,k}, i \le j \le k \qquad \text{Eq. 3-20}$$

$$m_{i,j} = m_{i,i+1} \times m_{i+1,i+2} \times \ldots \times m_{j-1,j}, i < j \qquad \text{Eq.3-21}$$

Proposition 2 indicates that a consistent multiplicative preference relation can be constructed from the set of $n-1$ values $\{m_{1,2}, m_{2,3}, \ldots, m_{n-1,n}\}$. A pairwise comparison matrix with entries in the interval $[1/v, v]$, $v > 0$ can be established. Then, the entries can be transformed into the interval $\left[1/9, 9\right]$ using a transformation function

$$f : \left[\frac{1}{v}, v\right] \rightarrow \left[\frac{1}{9}, 9\right], \quad f(x) = x^{1/\log_9 Z} \qquad \text{Eq. 3-22}$$

As described earlier in this section, risk analysts may have vague knowledge about the preference degree of one event over another, and cannot estimate their preferences with exact numerical values. It is more suitable to provide their preferences by means of linguistic variables rather than numerical ones. The disadvantage of this method is that the values in consistent multiplicative preference relation matrix are crisp, which cannot capture risk analysts imprecise judgements. Therefore, trapezoidal fuzzy numbers should be used as described in Section 3.2.2. The proposed fuzzy multiplicative consistency method is introduced in terms of trapezoidal fuzzy numbers.

3.4.2.2. Fuzzy multiplicative consistency method

A fuzzy multiplicative consistency method is proposed in this study in order to deal with inconsistencies in the risk decision making process. In this method, the multiplicative preference relation matrix $M = (m_{i,j}) = (a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j})$ is constructed based on consistent multiplicative preference relations as described earlier in section 3.4.2.1.

According to Buckley (1985), the consistency of a fuzzy reciprocal matrix is defined as

Definition 2: A fuzzy matrix $M = (m_{i,j})$ is reciprocal if and only if $m_{i,j} = m_{j,i}^{-1}$.

Definition 3: A fuzzy matrix $M = (m_{i,j})$ is consistent if and only if $m_{i,j} \otimes m_{j,k} \approx m_{i,k}$.

Proposition 3: Suppose a set of events, $A = (A_1, A_2, \cdots, A_n)$ associated with a fuzzy reciprocal multiplicative preference matrix $M = (m_{i,j}) = (a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j})$ with $a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j} \in [1/9, 9]$, the following statements are equivalent:

(1) $a_{i,j} = d_{j,i}^{-1} \quad \forall i, j \in (1,2,\cdots,n)$
(2) $b_{i,j} = c_{j,i}^{-1} \quad \forall i, j \in (1,2,\cdots,n)$
(3) $c_{i,j} = b_{j,i}^{-1} \quad \forall i, j \in (1,2,\cdots,n)$
(4) $d_{i,j} = a_{j,i}^{-1} \quad \forall i, j \in (1,2,\cdots,n)$

Proof. By Definition 2, $M = (m_{i,j})$ is a reciprocal fuzzy multiplicative preference matrix, $m_{i,j} = m_{j,i}^{-1} = 1 \varnothing m_{j,i}$, $\forall i, j \in (1,2,\cdots,n)$.

By using Eq. 3-7

$$m_{i,j} = (1,1,1,1) \varnothing (a_{j,i}, b_{j,i}, c_{j,i}, d_{j,i}), \forall i, j \in (1,2,\cdots,n)$$
$$((a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j}) = (1/d_{j,i}, 1/c_{j,i}, 1/b_{j,i}, 1/a_{j,i}) = (d_{j,i}^{-1}, c_{j,i}^{-1}, b_{j,i}^{-1}, a_{j,i}^{-1})$$
$$\therefore a_{i,j} = d_{j,i}^{-1}, b_{j,i} = c_{j,i}^{-1}, c_{i,j} = b_{j,i}^{-1}, d_{i,j} = a_{j,i}^{-1}, \forall i, j \in (1,2,\cdots,n)$$

Proposition 4: For a reciprocal fuzzy multiplicative preference relation $M = (m_{i,j}) = (a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j})$ to be consistent, the following statements are equivalent

(1) $a_{i,k} = a_{i,j} \times a_{j,k} \quad \forall i < j < k$
(2) $b_{i,k} = b_{i,j} \times b_{j,k} \quad \forall i < j < k$
(3) $c_{i,k} = c_{i,j} \times c_{j,k} \quad \forall i < j < k$
(4) $d_{i,k} = d_{i,j} \times d_{j,k} \quad \forall i < j < k$
(5) $a_{i,j} = a_{i,(i+1)} \times a_{(i+1),(i+2)} \times \cdots \times a_{(j-1),j} \quad \forall i < j$
(6) $b_{i,j} = b_{i,(i+1)} \times b_{(i+1),(i+2)} \times \cdots \times b_{(j-1),j} \quad \forall i < j$
(7) $c_{i,j} = a_{i,(i+1)} \times c_{(i+1),(i+2)} \times \cdots \times c_{(j-1),j} \quad \forall i < j$
(8) $d_{i,j} = d_{i,(i+1)} \times d_{(i+1),(i+2)} \times \cdots \times d_{(j-1),j} \quad \forall i < j$

Proof. By Definition 3, $M = (m_{i,j})$ is consistent then $m_{i,j} \otimes m_{j,k} = m_{i,k}$.

By using Eq. 3-6

$$m_{i,j} \otimes m_{j,k} = (a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j}) \otimes (a_{j,k}, b_{j,k}, c_{j,k}, d_{j,k})$$
$$= (a_{i,j} \times a_{j,k}, b_{i,j} \times b_{j,k}, c_{i,j} \times c_{j,k}, d_{i,j} \times d_{j,k}) = (a_{i,k}, b_{i,k}, c_{i,k}, d_{i,k}) = m_{i,k}$$
$$\therefore a_{i,k} = a_{i,j} \times a_{j,k}, b_{i,k} = b_{i,j} \times b_{j,k}, c_{i,k} = c_{i,j} \times c_{j,k}, d_{i,k} = d_{i,j} \times d_{j,k}, \forall i < j < k$$

The above expressions (1-4) are obtained and verified.

If $i < j$ and $k = j - i$, the expression (5) can be rewritten as

$$a_{i,j} = a_{i,(i+1)} \times a_{(i+1),(i+2)} \times \cdots \times a_{(i+k-1),(i+k)}$$

Mathematical induction is applied to prove expression (5) and assumptions are made as

If $k = 1$, then $a_{i,j} = a_{i,(i+1)}$

If $k = n$, by expression (1), then

$$\begin{aligned} a_{i,j} &= a_{i,(i+1)} \times a_{(i+1),(i+2)} \times \cdots \times a_{(i+n-1),(i+n)} \\ &= a_{i,(i+2)} \times a_{(i+2),(i+3)} \times \cdots \times a_{(i+n-2),(i+n-1)} \times a_{(i+n-1),(i+n)} \\ &= a_{i,(i++n-1)} \times a_{(i+n-1),(i+n)} = a_{i,(i+n)} = a_{i,j} \end{aligned}$$

If $k = n+1$, by using expression (1), then

$$\begin{aligned} a_{i,j} &= a_{i,(i+2)} \times a_{(i+2),(i+3)} \times \cdots \times a_{(i+n-1),(i+n)} \times a_{(i+n),(i+n+1)} \\ &= a_{i,(i+n)} \times a_{(i+n),(i+n+1)} \\ &= a_{i,(i+n+1)} = a_{i,j} \end{aligned}$$

The hypothesis is proved to be true when $k = 1, n$ and $n+1$, which completes the proof of the expression (5). Similarly, expressions (6-8) can be verified.

Proposition 4 shows that a comparison matrix can be established with $n-1$ preference trapezoidal fuzzy numbers in the interval $[1/v, v](v > 0)$. Therefore, a transformation function $f : [1/v, v] \rightarrow [1/9, 9]$ is needed to transfer trapezoidal fuzzy numbers in to the interval $[1/v, v]$ to $[1/9, 9]$:

(1) $f\left(1/v\right)=1/9.$

(2) $f\left(v\right)=9.$

(3) $f\left(x_a\right)\cdot f\left(y_d\right)=1\ \forall x_a, y_d \in\left[1/v,v\right]$ such that $x_a \cdot y_d =1$

(4) $f\left(x_b\right)\cdot f\left(y_c\right)=1\ \forall x_b, y_c \in\left[1/v,v\right]$ such that $x_b \cdot y_c =1$

(5) $f\left(x_c\right)\cdot f\left(y_b\right)=1\ \forall x_c, y_b \in\left[1/v,v\right]$ such that $x_c \cdot y_b =1$

(6) $f\left(x_d\right)\cdot f\left(y_a\right)=1\ \forall x_d, y_a \in\left[1/v,v\right]$ such that $x_d \cdot y_a =1$

(7) $f\left(x_a\right)\cdot f\left(y_a\right)= f\left(z_a\right)\ \forall x_a, y_a, z_a \in\left[1/v,v\right]$ such that $x_a \cdot y_a = z_a$

(8) $f\left(x_b\right)\cdot f\left(y_b\right)= f\left(z_b\right)\ \forall x_b, y_b, z_b \in\left[1/v,v\right]$ such that $x_b \cdot y_b = z_b$

(9) $f\left(x_c\right)\cdot f\left(y_c\right)= f\left(z_c\right)\ \forall x_c, y_c, z_c \in\left[1/v,v\right]$ such that $x_c \cdot y_c = z_c$

(10) $f\left(x_d\right)\cdot f\left(y_d\right)= f\left(z_d\right)\ \forall x_d, y_d, z_d \in\left[1/v,v\right]$ such that $x_d \cdot y_d = z_d$

It is well-known that the general solution verifying expressions (1) and (2) has the form

$f\left(x_a\right)=x_a{}^e$, being $e\in\Re.$

$f\left(x_b\right)=x_b{}^e$, being $e\in\Re.$

$f\left(x_c\right)=x_c{}^e$, being $e\in\Re.$

$f\left(x_d\right)=x_d{}^e$, being $e\in\Re.$

According to Eq. 3-8, the above expressions (1) and (2) can be rewritten as

$$f(x_a)=x_a{}^{1/\log_9^v},\ f(x_b)=x_b{}^{1/\log_9^v},\ f(x_c)=x_c{}^{1/\log_9^v},\ f(x_d)=x_d{}^{1/\log_9^v}$$

when $x_a \cdot y_d =1, x_b \cdot y_c =1, x_c \cdot y_b =1, x_d \cdot y_a =1$ the above expressions (3) to (6) can be verified

$$f\left(x_a\right)\cdot f\left(y_d\right)=x_a{}^{1/\log_9^v}\cdot x_d{}^{1/\log_9^v}=\left(x_a\cdot x_d\right)^{1/\log_9^v}=1^{1/\log_9^v}=1$$

$$f\left(x_b\right)\cdot f\left(y_c\right)=x_b{}^{1/\log_9^v}\cdot x_c{}^{1/\log_9^v}=\left(x_b\cdot x_c\right)^{1/\log_9^v}=1^{1/\log_9^v}=1$$

$$f\left(x_c\right)\cdot f\left(y_b\right)=x_c{}^{1/\log_9^v}\cdot x_b{}^{1/\log_9^v}=\left(x_c\cdot x_b\right)^{1/\log_9^v}=1^{1/\log_9^v}=1$$

$$f\left(x_d\right)\cdot f\left(y_a\right)=x_d{}^{1/\log_9^v}\cdot x_a{}^{1/\log_9^v}=\left(x_d\cdot x_a\right)^{1/\log_9^v}=1^{1/\log_9^v}=1$$

When $x_a \cdot y_a = z_a, x_b \cdot y_b = z_b, x_c \cdot y_c = z_c, x_d \cdot y_d = z_d$, the above expressions (7) to (10) will be

$$f(x_a)\cdot f(y_a) = x_a^{1/\log_9^v}\cdot y_a^{1/\log_9^v} = (x_a\cdot y_a)^{1/\log_9^v} = z_a^{1/\log_9^v} = f(z_a)$$
$$f(x_b)\cdot f(y_b) = x_b^{1/\log_9^v}\cdot y_b^{1/\log_9^v} = (x_b\cdot y_b)^{1/\log_9^v} = z_b^{1/\log_9^v} = f(z_b)$$
$$f(x_c)\cdot f(y_c) = x_c^{1/\log_9^v}\cdot y_c^{1/\log_9^v} = (x_c\cdot y_c)^{1/\log_9^v} = z_c^{1/\log_9^v} = f(z_c)$$
$$f(x_d)\cdot f(y_d) = x_d^{1/\log_9^v}\cdot y_d^{1/\log_9^v} = (x_d\cdot y_d)^{1/\log_9^v} = z_d^{1/\log_9^v} = f(z_d)$$

The following steps can be used to construct a consistent fuzzy multiplicative preference relation M for a set of events $A=(A_1, A_2, \cdots, A_n)$ and $n \geq 2$ on the basis of $n-1$ trapezoidal fuzzy numbers $\{m_{1,2}, m_{2,3}, \cdots, m_{(n-1),n}\}$.

Step 1: Let *X is* the preference values

$$X = \{m_{i,j}, i < j \wedge m_{i,j} \notin \{m_{1,2}, m_{2,3}, \cdots, m_{(n-1),n}\}$$
$$m_{i,j} = (a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j}\}$$
$$\left.\begin{aligned} a_{i,j} &= a_{i,(i+1)} \times a_{(i+1),(i+2)} \times \cdots \times a_{(j-1),j} \\ b_{i,j} &= b_{i,(i+1)} \times b_{(i+1),(i+2)} \times \cdots \times b_{(j-1),j} \\ c_{i,j} &= c_{i,(i+1)} \times c_{(i+1),(i+2)} \times \cdots \times c_{(j-1),j} \\ d_{i,j} &= d_{i,(i+1)} \times d_{(i+1),(i+2)} \times \cdots \times d_{(j-1),j} \end{aligned}\right. \qquad \forall i < j$$

Step 2: Calculate $v = \max(d_{i,j}), d_{i,j} \in m_{i,j}, m_{i,j} \in X$

Step 3: let $M' = \{m_{i,j}, m_{2,3}, \cdots, m_{n-1,n}\} \cup X \cup \{m_{i,j}, m_{2,3}, \cdots, m_{n-1,n}\}^{-1} X^{-1}$

Step 4: The consistent fuzzy multiplicative preference relation M can be obtained by $M = f(M')\ f: \left[\frac{1}{v}, v\right] \rightarrow \left[\frac{1}{9}, 9\right]$

, $f(x_a) = x_a^{1/\log_9 v}, f(x_b) = x_b^{1/\log_9 v}, f(x_c) = x_c^{1/\log_9 v}, f(x_d) = x_d^{1/\log_9 v}$

3.5 Summary

FRA and modified Fuzzy-AHP are discussed in this chapter. The fundamentals of FRA are described in terms of the concepts of fuzzy set, fuzzy number, linguistic variables, fuzzy rulebase and fuzzy inference process. The background of Fuzzy-AHP and the process of how modified Fuzzy-AHP is improved are proved and addressed. On the basis of these techniques, the developed railway safety risk model will be presented in the next chapter.

CHAPTER 4: DEVELOPMENT OF RAILWAY SAFETY RISK MODEL

4.1 Introduction

This chapter presents the developed railway safety risk model. Section 4.2 presents a proposed framework of safety risk model which includes the preliminary phase, design phase, FRA risk estimation phase, Fuzzy-AHP risk estimation phase and risk response phase. Four input parameters, failure frequency (FF), consequence severity (CS), consequence probability (CP), and weighting factor (WF) are discussed in section 4.2. Section 4.3 introduces an uncertainty expression. Section 4.4 introduces a important parameter of consequence probability CP, which is not currently taken into account in the risk assessment. At the end of the chapter, some features of the proposed railway risk model are summarised.

4.2 Improvement of Railway Safety Risk Model

A risk is the result of the error frequency combined with or multiplied by the severity of the consequence resulting from its occurrence (Peters et al, 2006). According to this definition, Risk Level (RL) can usually be assessed by considering two fundamental risk parameters, Failure frequency (FF) and Consequence severity (CS) (An et al, 2006 & 2007). However, it should be noted that the magnitude of a particular risk is also highly dependent on the probability that the effects will happen given by the occurrence of the failure. For example, small components such as shoe and brake gear detaching from train bogies is a highly frequent risk event (TLL, 2004). It could cause a derailment if the fallen shoes wedge in the points in conjunction with a serious failure of the signalling system. However, the probability that such a risk event causes a derailment is very low, as there is only a small chance that a fallen shoe would wedge in a point. So the risk event should be classified in the low risk category when taking into account the consequence probability, whereas without considering the consequence probability, such risk event will be classified in the high risk category, which would affect the risk ranking and disturb decision making. Therefore, the possibility of a current consequence from a particular failure should be taken into consideration in the risk assessment process in order to obtain a reliable result. In order to assess the risks associated with a railway system efficiently and effectively, a new risk parameter, consequence probability (CP) is proposed. The CP indicates the probability that a current consequence will happen given by the occurrence of the failure, which together with FF and CS are integrated into a fuzzy inference system (FIS) of fuzzy reasoning approach (FRA) to determine the RL of each hazardous event. The use of FRA allows imprecision or approximate information to be involved in the risk assessment process. In this method, a membership function (MF) is regarded as a possibility distribution based on a proposed theory; an apparent possibility distribution expressed by fuzzy set theory is transferred into a possibility measure distribution. The FRA method provides a useful tool for modelling risks and other risk parameters for risk analysis involving the risks with incomplete or redundant safety information (An et al, 2006 & 2007). Because the contribution of each hazardous event to the safety of a railway system is different, the weight of the contribution of each hazardous event should be taken into consideration in order to represent its relative contribution to the risk level (RL) of the railway system. Therefore, the weight factor (WF) is introduced, which indicates the magnitude of the relevant importance of a hazardous event or hazard group to its belongings in a risk tree. Fuzzy-AHP is employed to calculate the WFs during the process as described in Section 3.4. The application of Fuzzy-AHP may solve the problems of risk information loss in the hierarchical process so that risk assessment can be carried out from hazardous event level to a railway system level. Both of these processes result in a set of probability distributions, which can be used not only to predict RLs but also design safety maintenance intervals. The use of these techniques is especially appropriate in the railway environment because of the volume of experience, which is still available from long-term employees.

A risk assessment is a process that can be divided into five phases: the problem definition phase; data and information collection and analysis phase; hazard identification phase; risk estimation phase and risk response phase (An et al, 2007). This process provides a systematic approach to the identification and control of high-risk areas. According to this effective process, a risk assessment model based on FRA and Fuzzy-AHP approach for a railway system is proposed, as shown in Figure 4-1, where EI stands for Expert Index and UFN stands for Uniform Format Number, which are described in Section 4.2.3. The algorithm of the risk model consists of five phases: preliminary phase, FRA risk estimation phase, Fuzzy-AHP risk estimation phase and risk response phase.

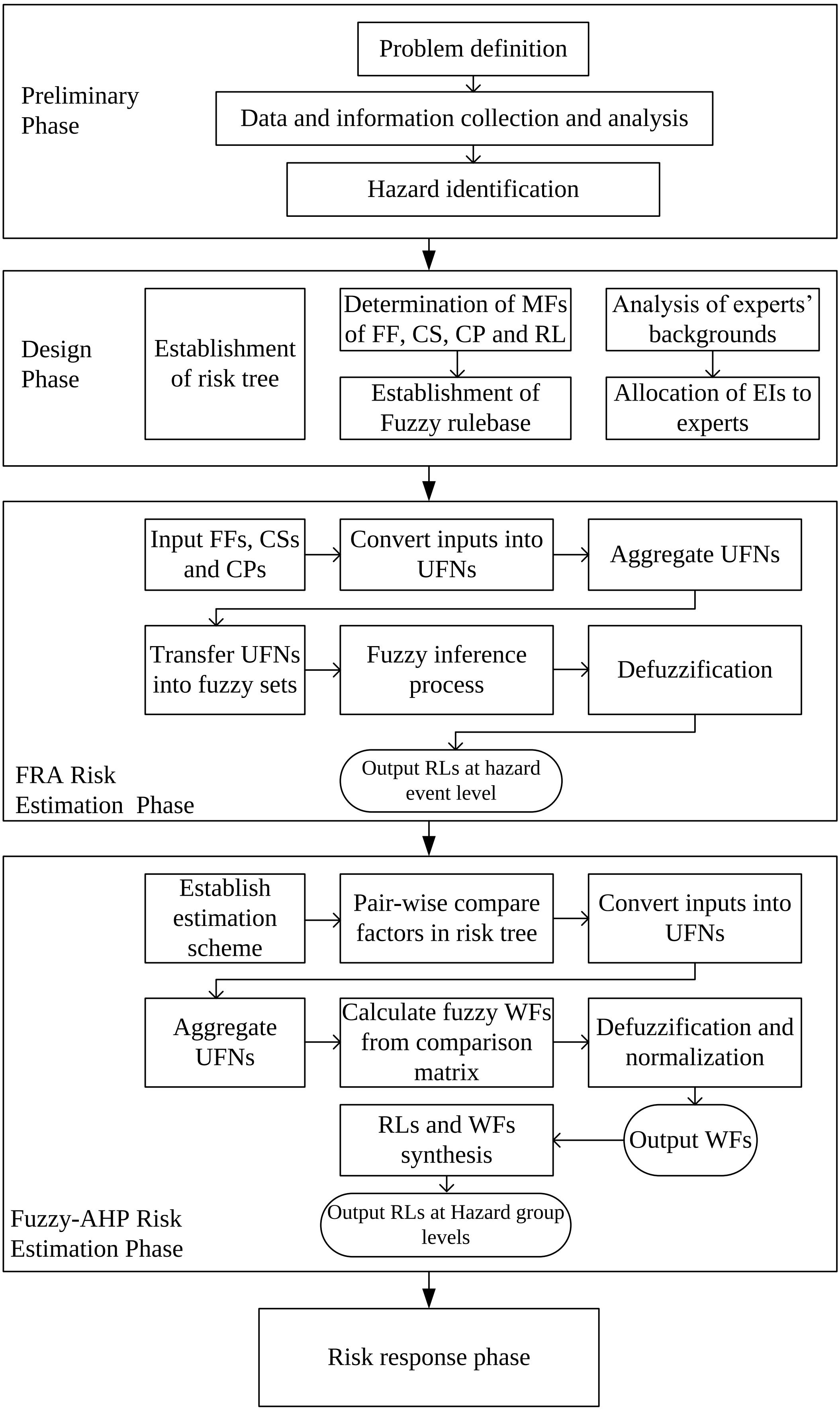


Figure 4-1 Risk assessment model

4.2.1 Preliminary phase

Risk assessment begins with problem definition which involves identifying the need for safety, i.e. specific safety requirements. The requirements regarding railway safety at different levels, e.g. hazardous event level, hazard group level and the railway system level, should be specified and made, which may include sets of rules and regulations made by national authorities and classification societies, deterministic requirements for safety, reliability, availability, maintainability, and criteria referring to probability of occurrence of serious hazardous events and the possible consequences (An et al., 2007; Chen et al., 2007).

Once the need for safety is established, the risk assessment moves from problem identification to data and information collection and analysis. The aim of data and information collection and analysis is to develop a good understanding of what serious accidents and incidents have occurred in a particular railway system over the years and generate a body of information. If the statistic data does not exist, expert and engineering judgements should be applied. The information gained from data and information collection will then be used to define the standards of qualitative descriptors and associated MFs of risk parameters, i.e. FF, CS, CP and RL. The design of risk parameters and the associated rule base are described in Section 4.2.2.2.

The purpose of hazard identification is to systematically identify all potential hazardous events associated with a railway system at each required level, e.g. hazardous event level, hazard group level, with a view to assessing their effects on railway system safety. Various hazard identification methods such as a brainstorming approach, check-list, 'what if?', HAZOP (Hazard and Operability), and failure mode and effect analysis (FMEA), may be used individually or in combination to identify the potential hazardous events for a railway system (HSE, 2001; Chen et al, 2007). The hazard identification can be initially carried out to identify hazardous events, and then progressed up to hazard group level and finally to the system level. The information from hazard identification will then be used to establish a risk tree, as described in Section 4.2.2.1.

4.2.2 Design phase

Once the risk information of a railway system is obtained in the preliminary phase, the risk assessment moves from the preliminary phase to the design phase. On the basis of information collection, the tasks in the design phase are to develop a risk tree and MFs of FF, CS, CP and RL and a fuzzy rule base.

4.2.2.1. Development of risk tree

There are many possible causes of risks that impact on railway system safety. The purpose of the development of a risk tree is to decompose these risk contributors into adequate details in which risks associated with a railway system can be efficiently assessed (Chen et al, 2007; An et al, 2008). A bottom-up approach is employed for the development of a risk tree. Figure 4-2 shows a typical risk tree that can be broken down into hazardous event level, hazard group level and system level. For example, hazardous events of E_1, E_2, …, E_n at hazardous event level affect the RL of S-HG_1 at sub-hazard group level, the RLs of S-HG_1, S-HG_2, …, S-HG_n contribute to the RL of HG_2 at hazard group level and RLs of HG_1, HG_2, …, HG_n contribute to the overall RL of a railway system at system level.

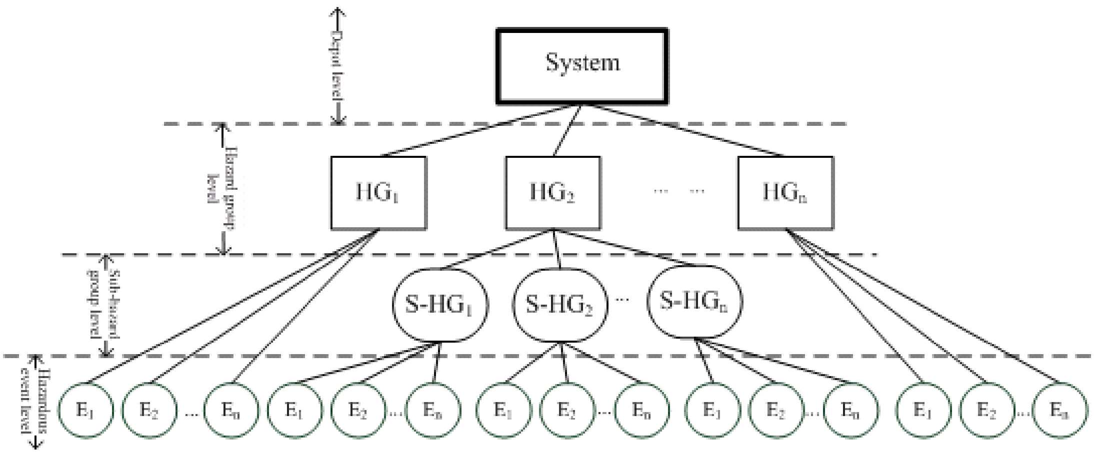


Figure 4-2 An example of a risk tree

4.2.2.2. Establishment of fuzzy rulebase

Fuzzy rule bases are basically built through the study of engineering knowledge, historical incident, and accident information. Human experts have a good intuitive knowledge of the system behaviour and the risks involved in various types of failures. A fuzzy rulebase is established in terms of qualitative descriptors of input parameters: FF, CS, CP and the output RL. The qualitative descriptors are characterised by fuzzy sets which are derived from experimental data or past information or characteristics of input or output variables, such as FF, CS, CP and RL. The fuzzy sets are defined in the universe of discourse and described by MFs. Currently, there are several geometric mapping functions widely adopted, such as triangular, trapezoidal and S-shaped MFs. However, triangular and trapezoidal MFs are the most frequently used in railway risk analysis practice (An et al., 2006 & 2007). For example, in the railway safety risk assessment, input parameters FF, CP, CS and output RL are constructed by trapezoidal MFs, which are determined according to characteristics of inputs or output variables as described in Section 4.3, where the input parameter FF is defined as “Remote”, “Rare”, “Infrequent”, “Occasional”, “Frequent”, “Regular”, and “Common”; CS is defined as “Negligible ”, “Marginal”, “Moderate”, “Critical”, and “Catastrophic”; CP is defined as “Highly unlikely”, “Unlikely”, “Reasonably unlikely”, “Likely”, “Reasonably likely”, “Highly likely” and “Definite”; the output RL is defined as “Low”, “Possible”, “Substantial”, and “High”. Rules using defined variables in the fuzzy rulebase are in IF-THEN format. For example, rule one is “IF FF is ‘Remote’ and CS is ‘Negligible’ and CP is ‘Highly unlikely’, THEN RL is ‘Low’”.

4.2.2.3. Allocation of EIs to experts

In practice, risk assessment usually involves a number of experts from different backgrounds or disciplines with essential experience regarding railway safety. Thus, these experts may have different impacts on the final decision. Expert Index (EI) is therefore introduced into the risk model to distinguish experts’ competence. The EI of *i-th* experts in *n* experts can be obtained by (Huang et al., 2007):

$$EI_i = \frac{RI_i}{\sum_{j=1}^{n} RI_j} \qquad \text{E.q. 4-1}$$

where RI_i is relevant importance of *i-th* expert according to experience, knowledge and expertise, which takes a value in the universe of [1, 9]. RI is defined in a manner that “1” means less importance, whereas “9” means most importance. Obviously, it is necessary to review EIs when the topic or the circumstance has changed.

4.2.3 FRA analysis

In the FRA risk estimation phase, each risk is assessed at hazardous event level based on FF, CS and CP to calculate its RL. However, railway risk analysts often face the circumstances where the risk data are incomplete or there is a high level of uncertainty involved in the risk data. A flexible method for expressing expert and engineering judgements is proposed (An et al., 2006 & 2008; Chen et al., 2007). The uniform format number (UFN) is introduced to capture and convert expert and engineering subjective judgements. As described earlier in this thesis, this allows imprecision or approximate information to be used in the risk analysis process. There are six steps to calculate the RLs of hazardous events that are described below.

Step 1: Input FFs, CSs, and CPs.

The input data can usually be gathered from historical data, however, in many circumstances, the data may not exist or uncertainty may be involved in the risk data. Experts may provide their judgements on the basis of their knowledge and expertise for each hazardous event (Herrera et al., 2001 & 2009; Zeng et al., 2007). The input values can be a precise numerical value, a range of numerical values or a linguistic term. For example, if adequate information is obtained and the risk factor is quantitative measurable, an expert is likely to provide a precise numerical value. However, experts sometimes find that it is hard to give numerical values due to uncertainties involved or the hazardous event is quantitative immeasurable, then a range of numerical values, a linguistic term or a fuzzy number can be used in the proposed model (An et al, 2006; Chen et al, 2007; Herrera et al, 2009), e.g. 'CP is 60% to 70%', 'CS is around 3 to 7 and most likely to be 5 in the universe of [0, 10]' and 'FF is average'.

Step 2: Convert inputs into UFNs.

As described at step 1, because the input values of hazardous events derived from experts' judgements are crisp, e.g. a numerical value, a range of numerical values, a fuzzy number, or a linguistic term, the UFN is employed to convert these experts' judgements into a uniform format for the composition of final decisions. UFN is developed based on a fuzzy trapezoidal number as it can represent most expert judgments.

A UFN can be defined as $A = \{a, b, c, d\}$, and its corresponding MF indicates the degree of preference and is defined as:

$$\mu_A(x) = \left\{ \begin{array}{ll} (x-a)/(b-a), & x \in [a,b], \\ 1 & x \in [b,c] \\ (x-d)/(c-d), & x \in [c,d], \\ 0, & otherwise. \end{array} \right\} \qquad \text{E.q. 4-2}$$

where four real numbers (*a*, *b*, *c*, and *d*) with satisfaction of the relationship $a \le b \le c \le d$ determine the x coordinates of the four corners of a trapezoidal membership function. It should be noted that a numerical value, a range of numerical values, a fuzzy number and a linguistic term can be converted as simplified UFN. Table 4-1 shows the possible expert judgements and their corresponding UFNs.

Expert Judgement	Input Values	Input type	UFNs
"…is *a*"	$\{a\}$	numerical value	$\{a, a, a, a\}$
"…is between *a* and *b*"	$\{a, b\}$	a range number	$\{a, (a+b)/2, (a+b)/2, a\}$
"…is between *a* and *c* and most likely to be *b*"	$\{a, b, c\}$	triangular fuzzy number	$\{a, b, b, a\}$
"… is between *a* and *d* and most likely between *b* and *c*"	$\{a, b, c, d\}$	trapezoidal fuzzy number	$\{a, b, c, d\}$
"… is *RARE*"	RARE	linguistic term	RARE MF $\{a, b, c, d\}$

Table 4-1 Experts' judgements and corresponding UFNs

Each UFN at this stage represents an opinion to one of the risk parameters of a hazardous event, which is given by an expert in a risk assessment on the basis of available information and personal subjective judgement.

Step 3: Aggregate UFNs.

The aim of this step is to apply an appropriate operator to aggregate individual judgements made by individual experts into a group judgement of each hazardous event. On the basis of experts' EIs calculated in the design phase, their judgments can be aggregated according to a weighted trapezoidal average formula (Bojadziev et al, 1997). Assume *m* experts involved in the assessment and *n* experts providing non-zero judgments for a hazardous event *i*, the aggregated UNF A^i can be determined by:

$$A^i = \{a^i, b^i, c^i, d^i\} = \left\{ \frac{\sum_{k=1}^{m} a_k^i EI_k}{\sum_{k=1}^{n} EI_k}, \frac{\sum_{k=1}^{m} b_k^i EI_k}{\sum_{k=1}^{n} EI_k}, \frac{\sum_{k=1}^{m} c_k^i EI_k}{\sum_{k=1}^{n} EI_k}, \frac{\sum_{k=1}^{m} d_k^i EI_k}{\sum_{k=1}^{n} EI_k} \right\}$$

$$A_k^i = \{a_k^i, b_k^i, c_k^i, d_k^i\} \quad \text{E.q. 4-3}$$

where a_k^i, b_k^i, c_k^i, and d_k^i are the numbers of UFNs A_k^i that represent the judgement of the *k-th* expert for hazardous event *i*. EI_k stands for *k*-th expert's EI.

Step 4: Transfer UFNs into fuzzy sets.

The FRA allows imprecision or approximate information, for example, expert and engineering judgements in the risk assessment process, which provides a useful tool for modelling risks and other parameters for risk analysis where the risk data are incomplete or include redundant information (Chen et al, 2007) . FRA here is employed to deal with UFNs of each hazardous event. In FRA, the aggregated UFNs of FF, CS, and CP are converted into matching fuzzy sets before being inputted into a fuzzy inference system. Assume A_{FF}^i, A_{CS}^i, and A_{CP}^i are three UFN of FF, CS and CP of hazardous event *i*, respectively. Their corresponding fuzzy sets $\tilde{A}_{FF}^i, \tilde{A}_{CS}^i$, and $\tilde{A}_{CP}^i$ are defined as:

$$\tilde{A}_{FF}^i = \left\{ \left(u, \mu_{A_{FF}^i}(u) \right) \mid u \in U = [0, u_n], \mu_{A_{FF}^i}(u) \in [0,1] \right\} \quad \text{E.q. 4-4}$$

$$\tilde{A}_{CS}^i = \left\{ \left(v, \mu_{A_{CS}^i}(v) \right) \mid v \in V = [0, v_n], \mu_{A_{CS}^i}(v) \in [0,1] \right\} \quad \text{E.q. 4-5}$$

$$\tilde{A}_{CP}^i = \left\{ \left(w, \mu_{A_{CP}^i}(w) \right) \mid w \in W = [0, w_n], \mu_{A_{CP}^i}(w) \in [0,1] \right\} \quad \text{E.q. 4-6}$$

where $\mu_{A_{FF}^i}, \mu_{A_{CS}^i}$, and $\mu_{A_{CP}^i}$ are trapezoidal MF of A_{FF}^i, A_{CS}^i, and A_{CP}^i respectively, and u, v, and w are input variables in the universe of discourse U, V, and W of FF, CS and CP, respectively.

Step 5: Fuzzy inference process

During the fuzzy inference process, these fuzzy sets of aggregated UFNs are then input to the fuzzy inference system to decide which rules are relevant to the current situation, and then calculate the fuzzy output of RL. The overall process is developed on the basis of the Mamdani method (Lee, 2005). The rules are stored in the rulebase which contains expert judgements and historical information. Relations between input parameters FF, CS, CP and output RL are presented in a form of if-then rules as described in Section 4.2.2.2. Supposing the *i*th rule in the rulebase is defined as:

$$R_i\text{: if } u \text{ is } \tilde{B}^i_{FF} \text{ and } v \text{ is } \tilde{B}^i_{CS} \text{ and } w \text{ is } \tilde{B}^i_{CP}\text{, then } x \text{ is } \tilde{B}^i_{RL},\ i = 1, 2, ..., n \qquad \text{E.q. 4-7}$$

where $u, v, w,$ and x are variables in the universe of discourse $U, V, W,$ and X of FF, CS, CP, and RL respectively, and $\tilde{B}^i_{FF}, \tilde{B}^i_{CS}, \tilde{B}^i_{CP},$ and $\tilde{B}^i_{RL}$ are qualitative descriptors of FF, CS, CP, and RL respectively. The calculation of the fire strength α_i of rule R_i with inputting fuzzy sets $\tilde{A}^i_{FF}, \tilde{A}^i_{CS}$, and $\tilde{A}^i_{CP}$ using fuzzy intersection operation is given by:

$$\alpha_i = \min\left[\max\left(\mu_{A'_{FF}}(u) \wedge \mu_{B^i_{FF}}(u)\right), \max\left(\mu_{A'_{CS}}(v) \wedge \mu_{B^i_{CS}}(v)\right), \max\left(\mu_{A'_{CP}}(w) \wedge \mu_{B^i_{CP}}(w)\right)\right]$$

E.q. 4-8

where $\mu_{A'_{FF}}(u), \mu_{A'_{CS}}(v)$, and $\mu_{A'_{CP}}(w)$ are the MFs of fuzzy sets $\tilde{A}^i_{FF}, \tilde{A}^i_{CS}$, and $\tilde{A}^i_{CP}$, respectively, and $\mu_{B^i_{FF}}(u), \mu_{B^i_{CS}}(v)$, and $\mu_{B^i_{CP}}(w)$ are the MFs of fuzzy sets $\tilde{B}^i_{FF}, \tilde{B}^i_{CS}$, and $\tilde{B}^i_{CP}$ of qualitative descriptors in rule R_i. After the fuzzy implication, the truncated MF $\mu'_{B^i_{RL}}$ of the inferred conclusion fuzzy set of rule R_i is obtained by:

$$\mu'_{B^i_{RL}}(x) = \alpha_i \wedge \mu_{B^i_{RL}}(x) \qquad \text{E.q. 4-9}$$

where α_i is the fire strength of rule R_i, and $\mu_{B^i_{RL}}(x)$ is the MF of qualitative descriptor $\tilde{B}^i_{RL}$ and x is an input variable in the universe of discourse X.

The firing strength is implicated with the value of the conclusion MF and the output is a truncated MF. The truncated MF's corresponding fuzzy sets which represent the implication output fuzzy sets of rules are aggregated into a single fuzzy set. The MF $\mu'_{B_{RL}}(x)$ of output fuzzy set after aggregation using fuzzy union (maximum) operation is denoted by:

$$\mu'_{B_{RL}}(x) = \overset{n}{\underset{i=1}{\mathrm{V}}} \mu'_{B_{RL}^{i}}(x) \qquad \text{E.q. 4-10}$$

where $\mu'_{B_{RL}^{i}}$ is the MF of conclusion fuzzy set of rule R_i and n is the total number of rules in the rule base.

Step 6: Defuzzification.

As the output from the fuzzy inference system is a fuzzy set, defuzzification is used to convert the fuzzy result into a matching numerical value that can adequately represent RL. The Centre of area method (Lee, 2005) is employed for defuzzification. Assume the output fuzzy set obtained from the fuzzy inference system is $\tilde{B}'_{RL} = \left\{ \left(x, \mu'_{B_{RL}}(x) \right) | \, x \in X, \mu'_{B_{RL}}(x) \in [0,1] \right\}$, the matching crisp value RL. RL^i of hazardous event *i* can be calculated by:

$$RL^i = \frac{\sum_{j=1}^{m} \mu'_{B_{RL}}(x_j) \cdot x_j}{\sum_{j=1}^{m} \mu'_{B_{RL}}(x_j)} \qquad \text{E.q. 4-11}$$

where *m* is the number of quantization levels of the output fuzzy set.

4.2.4 Fuzzy-AHP analysis

As stated earlier in Section 4.2, because the contribution of each hazardous event to the overall RL is different, the weight of the contribution of each hazardous event should be taken into consideration in order to represent its relative contribution to the RL of a railway system. The application of fuzzy-AHP may also solve the problems of risk information loss in the hierarchical process in determining the relative importance of the hazardous events in the decision making process, so that risk assessment can be progressed from hazardous event level to hazard group level, and finally to a railway system level. A fuzzy-AHP is an important extension of the traditional AHP method, which uses a similar framework to AHP to conduct risk analysis but fuzzy ratios of relative importance replace crisp ratios to the existence of uncertainty in the risk assessment. An advantage of fuzzy-AHP is its flexibility to be integrated with different techniques, for example, FRA techniques in risk analysis. In Section 3.4.2, an improved Fuzzy-AHP has been introduced, which will facilitate the use of typical Fuzzy-AHP. Therefore, an improved fuzzy-AHP analysis leads to the generation of WFs for representing the primary hazardous events within each category. There are six steps to calculate WFs as described below.

Step 1:Eestablish estimation scheme.

Fuzzy-AHP determines WFs by conducting pairwise comparison. The comparison is based on an estimation scheme, which lists intensity of importance using qualitative descriptors. Each qualitative descriptor has a corresponding triangular MF that is employed to transfer expert judgments into a comparison matrix (An et al, 2007). Table 4-2 describes qualitative descriptors and their corresponding triangular fuzzy numbers for risk analysis at railway depots. Each grade is described by an important expression and a general intensity number. When two risk contributors are of equal importance, it is considered (1,1,2). Fuzzy number (8,9,9) describes that one risk contributor is absolutely more important than the other. Figure 4-3 shows triangular MFs (solid lines) with "*equal importance*"–(1,1,2), "*weak importance*"–(2,3,4), "*strong importance*"–(4,5,6), "*very strong importance*"–(6,7,8) and "*absolute importance*"–(8,9,9), respectively. The other triangular MFs (dash lines) describe the corresponding intermediate descriptors between them.

Qualitative descriptors	Description	Parameters of MFs (triangular)
Equal importance (EQ)	Two risk contributors contribute equally to the shunting event	(1,1,2)
Between equal and weak importance (BEW)	When compromise is needed	(1,2,3)
Weak importance (WI)	Experience and judgment slightly favour one risk contributor over another	(2,3,4)
Between weak and strong importance (BWS)	When compromise is needed	(3,4,5)
Strong importance (SI)	Experience and judgment strongly favour one risk contributor over another	(4,5,6)
Between strong and very strong importance (BSV)	When compromise is needed	(5,6,7)
Very strong importance (VI)	A risk contributor is favoured very strongly over the other	(6,7,8)
Between very strong and absolute importance (BVA)	When compromise is needed	(7,8,9)
Absolute importance (AI)	The evidence favouring one risk contributor over another is of the highest possible order of affirmation	(8,9,9)

Table 4-2 Fuzzy-AHP estimation scheme

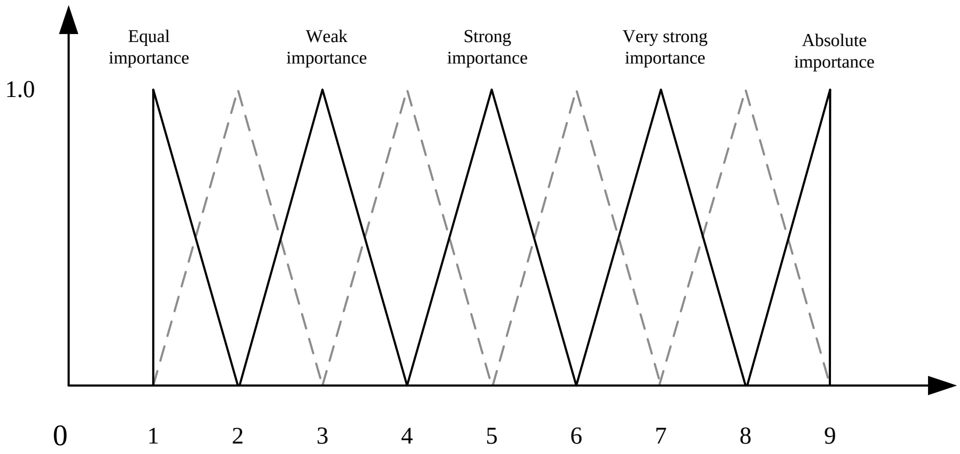


Figure 4-3 MFs of qualitative descriptors in fuzzy-AHP estimation scheme

Step 2: Pair-wise compare factors in risk tree

“HG_1”, “HG_2”,..., and “HG_n” as shown in Figure 4-2 are the risk contributors that contribute to the overall RL of a railway system. Assume two risk contributors HG_1 and HG_2, if HG_1 is very strong importance more than HG_2, a fuzzy number of (6,7,8) is then assigned to HG_1 based on the estimation scheme as shown in Table 4-2. Obviously, risk contributor HG_2 has a fuzzy number of (1/8,1/7,1/6). Suppose *n* risk contributors, there are a total of $N = n - 1$ pairs which need to be compared due to the benefits of applying improved Fuzzy-AHP. The following classifications can be used in the comparison.

-. A numerical value, e.g. “3”

-. A linguistic term, e.g. “strong importance”.

-. A range, e.g. (2, 4), the scale is likely to be between 2 and 4.

-. A fuzzy number, e.g. (2, 3, 4), the scale is between 2 and 4, most likely 3 or (2, 3, 4, 5), the scale is between 2 and 5, most likely between 4 and 5.

-. 0, e.g. the two risk contributors cannot be compared at all.

Step 3: Convert inputs into UFNs.

As described at steps 1 and 2, because the values of risk contributors are crisps, e.g. a numerical value, a range of numerical values, a linguistic term or a fuzzy number, the FRA is employed again to convert these values into UFNs according to Table 4-1. A series of UFNs can be obtained to correspond to the scores and the scales of the defined risk contributors in the risk tree.

Step 4: Aggregate UFNs.

Usually, there are a number of experts in the risk assessment group and their judgments may be different. Therefore, UFNs produced at step 3 need to be aggregated into a group UFN for each risk contributor. The process is same as described in Section 4.2.3 at step 3.

Step 5: Calculate fuzzy WFs from comparison matrix.

The aggregated UFN are then used to construct a comparison matrix. Suppose

$C_1, C_2, ..., C_n$ are risk factors in a hazard group *p*, $A_{i,j}$ is the aggregated UFN representing the quantified judgement on C_i comparing to C_j and C_i is more important than C_j. By applying the improved Fuzzy-AHP, there will be $n-1$ aggregated UFN, i.e. $A_{1,2}, A_{2,3}, ..., A_{i,j}, A_{j,j+1}, ..., A_{n-1,n}$. Then, following steps 1 to 4 in Section 3.4.2.2, an entire comparison matrix for the hazard group *p* can be developed. The pairwise comparison between C_i and C_j in the hazard group *p* thus yields a $n \times n$ matrix defined as

$$M = \left[A_{i,j}\right] = \begin{bmatrix} A_{1,1} & A_{1,2} & \cdots & A_{1,n} \\ A_{2,1} & A_{2,2} & \cdots & A_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n,1} & A_{n,2} & \cdots & A_{n,n} \end{bmatrix}, i, j = 1, 2, \ldots, n \qquad \text{E.q. 4-12}$$

$$A_{i,j} = \left\{a_{i,j}, b_{i,j}, c_{i,j}, d_{i,j}\right\}, A_{j,i} = \left\{1/a_{i,j}, 1/b_{i,j}, 1/c_{i,j}, 1/d_{i,j}\right\}$$

where $a_{i,j}, b_{i,j}, c_{i,j},$ and $d_{i,j}$ are the numbers of UFN $A_{i,j}$.

Then, the WFs can be calculated by the geometric mean technique (Bojadziev et al, 1997). The UFN geometric mean $\bar{A}_i$ of the *i*-th row in the comparison matrix is defined as:

$$\bar{A}_i = \left\{\bar{a}_i, \bar{b}_i, \bar{c}_i, \bar{d}_i\right\} = \left\{\sqrt[n]{\prod_{j=1}^{n} a_{i,j}}, \sqrt[n]{\prod_{j=1}^{n} b_{i,j}}, \sqrt[n]{\prod_{j=1}^{n} c_{i,j}}, \sqrt[n]{\prod_{j=1}^{n} d_{i,j}}\right\} \qquad \text{E.q. 4-13}$$

$$W_i = \left\{a_i, b_i, c_i, d_i\right\} = \left\{\frac{\bar{a}_i}{\sum_{j=1}^{n} \bar{d}_j}, \frac{\bar{b}_i}{\sum_{j=1}^{n} \bar{c}_j}, \frac{\bar{c}_i}{\sum_{j=1}^{n} \bar{b}_j}, \frac{\bar{d}_i}{\sum_{j=1}^{n} \bar{a}_j}\right\} \qquad \text{E.q. 4-14}$$

Where W_i is the fuzzy WF of C_i.

Step 6: Defuzzification and normalisation.

Because the outputs of geometric mean methods are fuzzy WFs, a defuzzification is adopted to convert fuzzy WFs to matching crisp values in which the fuzzy AHP employs a defuzzification approach proposed (Bojadziev et al., 1997). The crisp value w_i' of fuzzy WF can be calculated by:

$$w_i' = \frac{a_i + 2\left(b_i + c_i\right) + d_i}{6} \qquad \text{E.q. 4-15}$$

The final WF of C_i is obtained by:

$$WF_i = \frac{w_i'}{\sum_{j=1}^{n} w_j'} \qquad \text{E.q. 4-16}$$

Step7: Calculate RLs of sub-hazard groups.

Once the WFs of risk contributors are obtained, the overall RL at sub-hazard group can be calculated by the synthesising of WF and RL for each hazardous event produced in the FRA risk estimation phase. The RL of a sub-hazard group $S-HG_i$ is defined by

$$RL_{S-HG_i} = \sum_{i=1}^{n} RL_{C_i} WF_{C_i} \quad i = 1,2,\cdots,n \qquad \text{E.q. 4-17}$$

where RL_{C_i} and WF_{C_i} are the RL and WF of C_i .

Similarly, WF_{S-HG_i} of sub-hazard groups and WF_{HG_i} of hazard groups can be obtained by repeating steps 1 to 7. The RLs of hazard groups and the overall RL of a railway system can be obtained by

$$RL_{HG_i} = \sum_{i=1}^{n} RL_{S-HG_i} WF_{S-HG_i} \quad i = 1,2,\cdots,n$$ E.q. 4-18

$$RL_{System} = \sum_{i=1}^{n} RL_{HG_i} WF_{HG_i} \quad i = 1,2,\cdots,n$$ E.q. 4-19

where RL_{HG_i} and WF_{HG_i} are the RL and WF of the *i*th hazard group HG_i, RL_{S-HG_i} and WF_{S-HG_i} are the RL and WF of the *i*th sub-hazard group and RL_{System} is the overall RL of the railway system.

4.2.5 Risk response phase

The results produced from the risk estimation phases may be used through the risk response phase to assist risk analysts, engineers and managers in developing maintenance and operation policies. If risks are high, risk reduction measures must be applied or the depot operation has to be reconsidered to reduce the occurrence probabilities or to control the possible consequences. However, the acceptable and unacceptable regions are usually divided by a transition region. Risks that fall in this transition region need to be reduced to as low as reasonably practicable (ALARP) (LUL, 2001; Muttram et al, 2002; Railway Safety, 2003). In this study, the RLs are characterised into four regions, i.e. ‘High’, ‘Substantial’, ‘Possible’ and ‘Low’.

4.3 Introduction to Third Parameter CP

Currently, there are many applications which use two parameters, such as failure likelihood and consequence severity, to evaluate the risk (Huang et al, 2005; An et al, 2006). However, in many circumstances, these applications may not give satisfactory results because a hazard event may cause several consequence scenarios with various levels of severity, and there is high level of uncertainty involved in determining the probability of a possible consequence scenario occurring. In those applications, as failure likelihood is defined as the number of times an event occurs over as a specified period of time, without considering the probability of causing a current scenario, the risk event with very high failure frequency and consequence severity but very low consequence probability will always be mistaken as the event with very high risk. Therefore, it is essential to further improve the proposed railway safety risk assessment model to identify major hazards and assess the associated risks more effectively and efficiently.

The Australian standard for risk management (AS/NZS 4360:1999) suggests that it is appropriate to consider the likelihood to be composed of two elements, usually referred to as frequency of exposure and probability. Frequency of exposure is the extent to which a source of risk exists, and probability is the chance that when that source of risk exists, consequences will follow. That means the risk assessment could be carried out based on three parameters, including the severity of consequence. Currently, there are some existing applications which apply three parameters for risk assessment in many areas. Stephen Heller uses three parameters to manage industrial risk where hazard events are assessed in terms of exposure rating weight, probability, and consequence (Heller, 2006). Exposure rating weight is the frequency of occurrence of the hazard event. Probability is the likelihood accident sequence that will follow to completion. Consequence is the period of loss of operations. The risk score of each hazard event is the multiplication of these three parameters. In the offshore sector, the risk assessment is also carried out based on three parameters (An et al., 2000). In the application, the risk to each component failure is assessed by three parameters including failure severity which describes the magnitude of possible consequences, failure rate which defines the failure times in a certain period, and failure consequence probability which defines the probability that the effects will happen given by the occurrence of the failure. In the railway sector, these similar parameters are also considered in Fault tree and Event tree analysis (Muttram, 2002).

In a comparison with the applications using two parameters in the risk assessment, it is worth noting that by using three parameters could help risk analysts with likelihood analysis and risk control measures that are designed to reduce the likelihood aspect of risk, since the failure frequency and the consequence probability of a hazard event, which determine the likelihood of risk event, are considered independently in the risk assessment. A hazard event with very high occurrence frequency but very low consequence probability, or with very low occurrence frequency but very high consequence probability can be reasonably evaluated effectively. It is therefore appropriate to use three parameters in the proposed railway safety risk model to assess the risk of each hazard event.

The proposed three parameters in the model are Failure Frequency (FF), Consequence Severity (CS), and Consequence Probability (CP). The Risk Level (RL) of a hazard event is derived from the combination of these three parameters. As the risk model is developed based on a FRA and Fuzzy-AHP combined approach, for each parameter, membership functions and linguistic terms are designed as follows:

FF defines the number of times an event occurs over a specified period, e.g. number of events/year. Table 4-3 describes the range of frequencies of failure occurrence. To estimate the failure occurrence, one may often use such linguistic variables as "*remote*", "*rare*", "*infrequent*", "*occasional*", "*frequent*", "*regular*" and "*common*" (Huang et al, 2005; An et al, 2007). For example, linguistic variable *infrequent* is defined to cover the likelihood ranging from occurring once every 35 years to occurring approximately once every 7 years. As the linguistic variables are categorised according to a range of FF, the trapezoidal MFs are assigned to characterise these linguistic variables. Figure 4-4 shows the fuzzy FF set definition.

Linguistic values	Description	Mid-point of the estimated frequency	Approximate numerical value (event/yr)	Parameters of MFs (trapezoid)
Remote	< 1 in 175 years	1 in 500 years	0.002	0, 0, 2E-3, 6E-3
Rare	1 in 35 years to 1 in 175 years	1 in 100 years	0.01	2E-3, 6E-3, 1.5E-2, 4E-2
Infrequent	1 in 7 years to 1 in 35 years	1 in 20 years	0.05	1.5E-2, 4E-2, 8E-2, 2E-1
Occasional	1 in 1 ¼ years to 1 in 7 years	1 in 4 years	0.25	8E-2, 2E-1, 5E-1, 1.25
Frequent	1 in 3 months to 1 in 1 ¼ years	1 in 9 months	1.25	5E-1, 1.25, 2.25, 5.25
Regular	1 in 20 days to 1 in 3 months	1 in 2 months	6.25	2.25, 5.25, 10.25, 31.25
Common	1 in 4 days to 1 in 20 days	1 in 12 days	31.25	10.25, 31.25, 100, 100

Table 4-3 Failure frequency

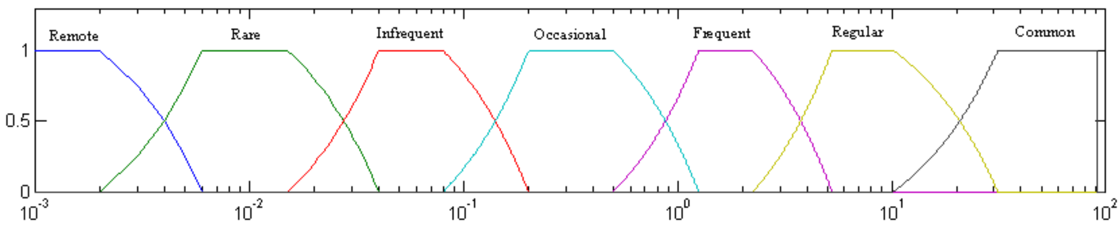


Figure 4-4 Failure frequency

CS describes the magnitude of possible consequences. For example, in many cases, it can be represented as the number of fatalities, major injuries and minor injuries resulting from the occurrence of a particular hazardous scenario. One may often use such linguistic variables as "*negligible*", "*marginal*", "*critical*", "*moderate*" and "*catastrophic*" to describe consequence severity (Huang et al, 2005; An et al, 2007). The definitions of linguistic variables about CS are listed in Table 4-4. For example, linguistic variable *negligible* is defined to describe a hazard event with negligible system damage and/or no injury and with a numerical value range from 0 to 0.1. The numerical values in Table 4-4 are the combination values of equivalent fatalities (EFs) in which a minor injury equals to 0.01 EF and a major injury equals to 0.1 EF. The trapezoidal MFs as shown in Figure 4-5 are employed to characterise CS, and their parameters are based on the numerical values listed in Table 4-4.

Linguistic values	Description	Numerical value (event/yr)	Parameters of MFs (trapezoid)
Negligible	No injury and/or negligible damage to the system	0–0.1	0, 0, 9E-2, 1E-1
Marginal	Minor system damage and/or minor injury	0.1–2	9E-2, 1E-1, 1, 2
Moderate	Failure causes some operational dissatisfaction and/or major injury	2–5	1, 2, 4, 5
Critical	Major system damage and/or severe injury	5–10	4, 5, 9, 10
Catastrophic	System loss and/or fatality	>10	9, 10, 60, 60

Table 4-4 Consequence severity

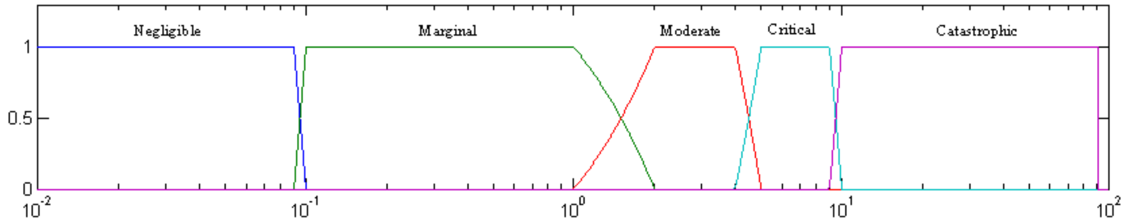


Figure 4-5 Consequence severity

CP defines the probability that the effects will happen given by the occurrence of the failure. Such linguistic variables as "*Highly unlikely"*, "*Unlikely*", "*Reasonably unlikely*", "*Likely*", "*Reasonably likely*", "*Highly likely*" and "*Definite*" may be used (An et al, 2000). Table 4-5 shows the evaluation criteria of consequence probability for the rankings and the corresponding linguistic terms. Figure 4-6 below gives the fuzzy CP set definition, where the trapezoidal membership functions are used to characterise CP.

Linguistic values	Description	Parameters of MFs (trapezoid)
Highly unlikely	The occurrence likelihood of accident is highly unlikely.	0.00, 0.00, 0.15, 0.20
Unlikely	The occurrence likelihood of accident is unlikely but possible given the occurrence of the failure event.	0.15, 0.20, 0.25, 0.30
Reasonably unlikely	The occurrence likelihood of accident is between likely and unlikely.	0.25, 0.30, 0.35, 0.425
Likely	The occurrence likelihood of accident is likely.	0.35, 0.425, 0.575,0. 65
Reasonably likely	The occurrence likelihood of accident is between likely and highly likely.	0.575, 0.65, 0.70, 0.75
Highly likely	The occurrence likelihood of accident is very likely	0.70, 0.75, 0.80, 0.85
Definite	The accident occurs given the occurrence of the failure event.	0.80, 0.85, 1.00, 1.00

Table 4-5 Consequence probability

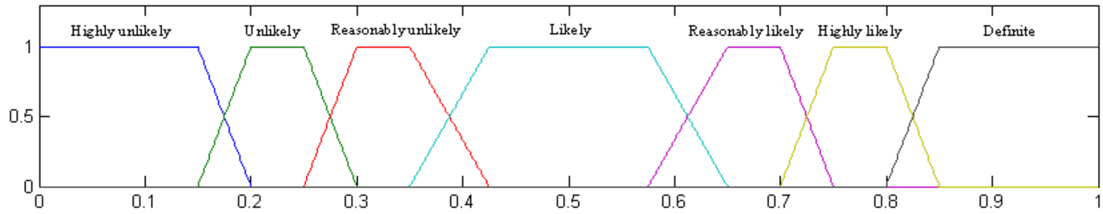


Figure 4-6 Consequence probability

4.4 Summary

The chapter introduces a new railway safety risk model, which is developed based on the bottom-up approach. Four input parameters (FF, CP, CS, WF) to assess the risks from the component level to the system level are described. The CP parameter is introduced to improve the risk ranking. The risk model allows experts to use numerical numbers, fuzzy numbers, or even linguistic terms in the risk assessment. The results produced from the proposed risk model are in the format of risk scores and risk categories as well as risk contributions, while the conventional techniques can only give the risk score, with its meaning being difficult to understand. A software package has been developed based on the proposed model to facilitate risk assessment, which will be presented in the next chapter.

CHAPTER 5: SOFTWARE DEVELOPMENT BASED ON PROPOSED RAILWAY SAFETY RISK MODEL

5.1 Introduction

In order to provide a systematic tool for railway safety risk assessment, a software based on the proposed risk model is developed. This chapter describes the software development based on the proposed safety risk model.

5.2 Development of the Software

A railway intelligent safety risk assessment system (RISRAS) has been developed based on the proposed risk analysis model. It is designed to aid the railway risk assessment process via a user-friendly interface, hence no knowledge of the manner in which the data are stored and manipulated is required. The system has been developed using Microsoft Visual C++ and operates under Microsoft Windows 2000, NT, XP or Vista. The architecture of RISRAS has been designed to ensure that the system is adaptable and upgradeable so that customisation of the system can be easily carried out. The current system is generic, but it is acknowledged that individuals or corporations will prefer specific systems based on the rules in the particular cases. In order to minimise system changes and maintain the flexibility and scalability of the system, it is designed on the basis of three-layer architecture (Dewire. 1993; An et al, 2008): i.e. presentation logic layer, application logic layer and database layer as shown in Figure 5-1. The presenter can be thought of much like a web-browser that performs many functions involving user-interaction at the presentation logic layer, but the bulk of the processing work is done behind the scenes; in this case, it is the risk assessment server which consists of a number of modules at application logic and database layers. The risk assessment server application controls the data and information flow between the presenter and the data stores/sources, which effectively forms the heart of the RISRAS. This is particularly useful as using such a three-layer architecture in the system allows other modules to be developed and added into the system conveniently. The main benefit of using such architecture is that the data and analytical process are completely separated from the user. This independence enables modifications to be made to each of the modules individually, with little or no impact on others. The roles of each layer are discussed in the following sections.

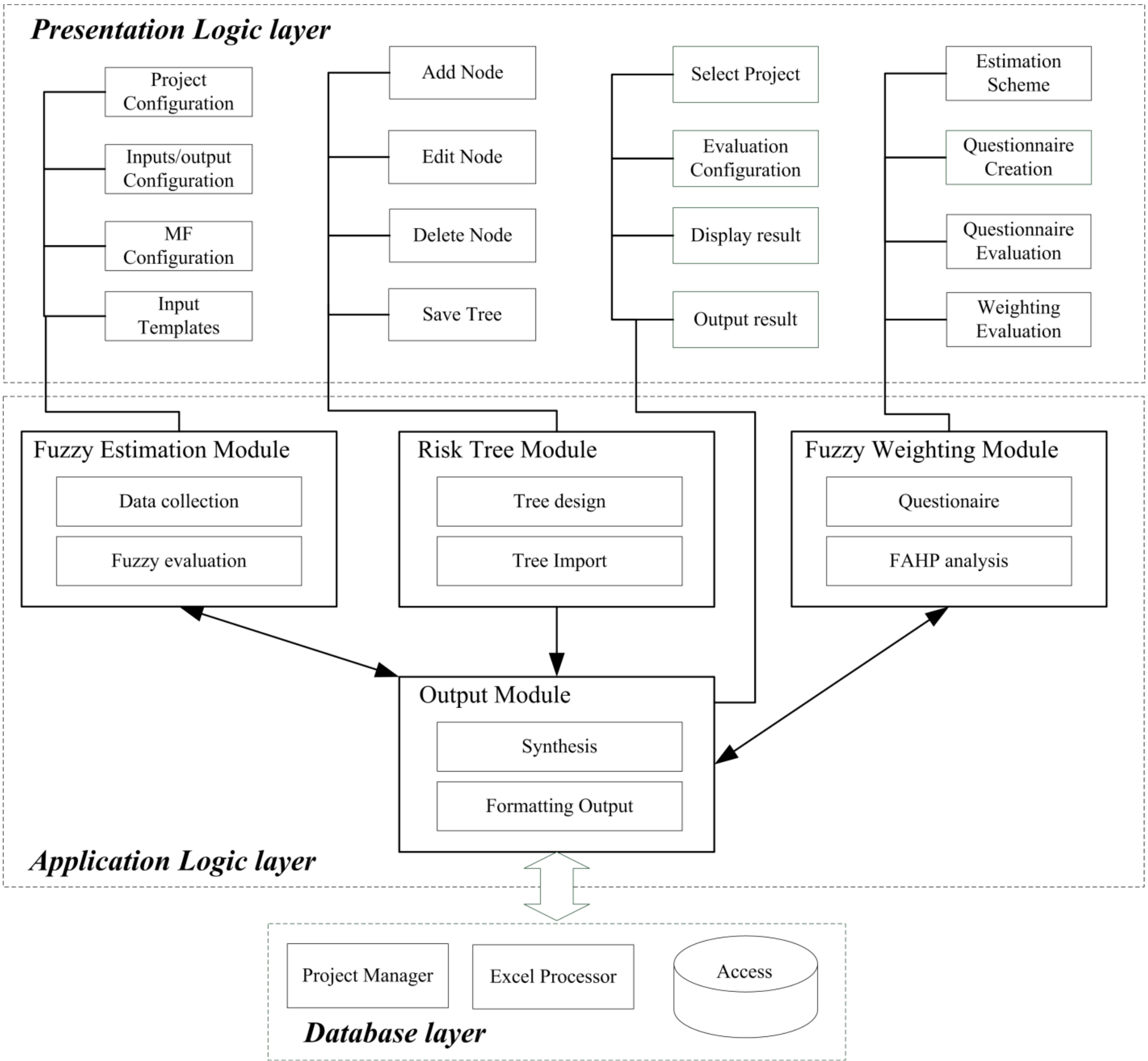


Figure 5-1 System architecture

5.2.1 Presentation logic layer

The presentation logic layer provides the user with a user-friendly interface to aid the railway risk assessment process. The presenter controls the graphical user interface, with which the user can interact in order to perform the risk assessment process. The presenter application makes a call to the sever then communicates with other layers through several input/output functional modules, i.e. '*Risk Tree Module* (RTM)', '*Fuzzy Estimation Module* (FEM)', '*Fuzzy Weighting Module* (FWM)' and '*Output Module* (OM)' as shown in Figure 5-1.

As stated earlier in this thesis, the RLs of hazard groups affect the overall RL of a railway system, which can be further broken down into sub-hazard groups in order to identify all possible hazardous events. The risk assessment can initially be carried out from hazardous event level and then progressed up to sub-hazard group level, hazard group level and finally to system level. The RTM module allows the user to create a risk tree that links by risk nodes. In this case, they are hazardous events, sub-hazard groups and hazard groups with relevant information, i.e. belongings and descriptions.

The FEM module consists of four sub-functional modules to process the FRA evaluation. The '*Project Configuration*' defines the input risk parameters, i.e. FF, CP and CS. The '*Input/output configuration*' defines the output RL in the risk assessment. The '*MF Configuration*' defines the MFs to describe risk qualitative descriptors, fuzzy rules and fuzzy operations, which can be specified for a particular case. As there could be a large amount of risk data involved in the risk analysis, the system provides an '*Input Template*' functional module, using which the user can easily input data manually or transfer data from an existing Microsoft Excel file to the system.

As stated earlier in this thesis, Fuzzy-AHP is employed to determine the relative importance of risk factors in order to synthesise the contributions of risks at hazardous event level to hazard group level and finally to a railway system level. The FWM module has four functional modules. The '*Estimation Scheme*' defines the estimation scheme as described in Section 4.2.4. It allows users to add or modify MFs to create new scheme for a particular case. The '*Questionnaire Creation*' can generate a Microsoft Excel file on the basis of selected risk factors from the risk tree and then the '*Questionnaire Evaluation*' creates a Fuzzy-AHP comparison matrix automatically by the system. The WF of each risk factor can finally be derived from the '*Weight Evaluation*' functional module.

The results of FRA and Fuzzy-AHP analysis will finally be synthesised to obtain an overall RL of a railway system. There are four functional modules in the OM module, which enable the user to view and store the results into the database. The user can use the '*Select Project*' functional module to manage risk trees and risk information established previously, which enables the user to choose and re-use these risk trees and risk information in the future analysis. The user can also determine whether WFs should or not be taken into consideration in the assessment process by selecting the '*Evaluation Configuration*' functional module. The "*Output Result*" functional module enables the user to display and save the results in a Microsoft Excel file.

5.2.2 Application logic layer

The application logic layer consists of four modules to manipulate the data and information flow. The FEM is developed based on the proposed risk model using the FRA approach to compute the RLs of hazardous events as described in Section 2.3. The '*Data Collection*' sub-module takes the input data from a Microsoft Excel file via an Open DataBase Connectivity (ODBC) connection to the database (Dewire. 1993; An et al, 2008). The '*Fuzzy Evaluation*' sub-module performs the FRA risk estimation. RTM manages the risk trees established in the risk analysis. By using the '*Risk Tree Design*' sub-module, the user can create a risk tree for a particular case and the '*Risk Tree Import*' sub-module delivers the risk trees to OM. The FWM is designed based on the fuzzy-AHP approach proposed in the risk model as described in Section 4.2, which is used to quantify expert judgements and calculate the WFs. The ‘*Questionnaire*’ sub-module provides users with a template in an excel format via an ODBC connection. Users can easily fill in the expert opinions on the template and then the ‘*FAHP Analysis*’ sub-module calculates the WFs and produces a fuzzy-AHP comparison matrix. OM manages data flow in the risk assessment process and presents the results. The ‘*Synthesis*’ sub-module ensures that the assessment is performed from hazardous event level then progressed up to sub-hazard group level, hazard group level and finally to railway depot level according to the risk tree established in RTM by synthesising the RLs of hazardous events derived from FEM and the WFs from FWM. The ‘*Formatting Output*’ sub-module manages the format of the output of the results to a Microsoft Excel file via an ODBC connection.

5.2.3 Database layer

Data is clearly fundamental to the operation of the RISRAS system. The database stores most of data and information that RISRAS uses, such as risk tree, risk parameters, and WFs etc. The database chosen for the system is Microsoft Access. This package was selected for several reasons, including its popularity as a user-friendly relational database within industry, the fact that it is available at a reasonable cost and its easy access via an ODBC connection (Dewire. 1993; An et al, 2008). The “*Excel Processor*” module provides the functions to input and output data from or to a Microsoft Excel file. The “*Project Manager*” manipulates project data including the configurations of FRA and fuzzy-AHP in the RISRAS system as well the details of the risk trees.

5.3 Application of the Software to Railway Safety Risk Assessment

5.3.1 Risk identification

Risk assessment begins with an identified need. Problem definition involves identifying the need for safety, i.e. specific safety requirements. The requirements regarding safety should be specified and they may have to be made at different levels, e.g. component level, sub-system level and system level in order to identify all possible failure events. Users can easily use the proposed RISRAS to build up a risk tree at component level, sub-system level and system level via a graphical user-friendly interface as described in Section 5.2.1. For example, Figure 5-2 shows a risk tree that consists of a number of sub-systems and each sub-system has a number of components, which are inside the nodes. In this example, failure events of the component “Formation_layer” affect its risk at component level. Risks of “Formation_layer” and “Base” affect the risk of “Foundation” at sub-system level and risks of “Track_component” and “Foundation” affect the risk of “Track system” at system level, hence the risk tree for components, subsystems and the system is defined. The actual effects of failure events and risks are dependent on their FF, CP, CS and the relative importance of failure events, i.e. WFs. The establishment of a risk tree user interface, as shown in Figure 5-2, enables the user to systematically identify all potential failure events associated with a railway system at component level and subsystem level with a view to assessing their effects at railway system level.

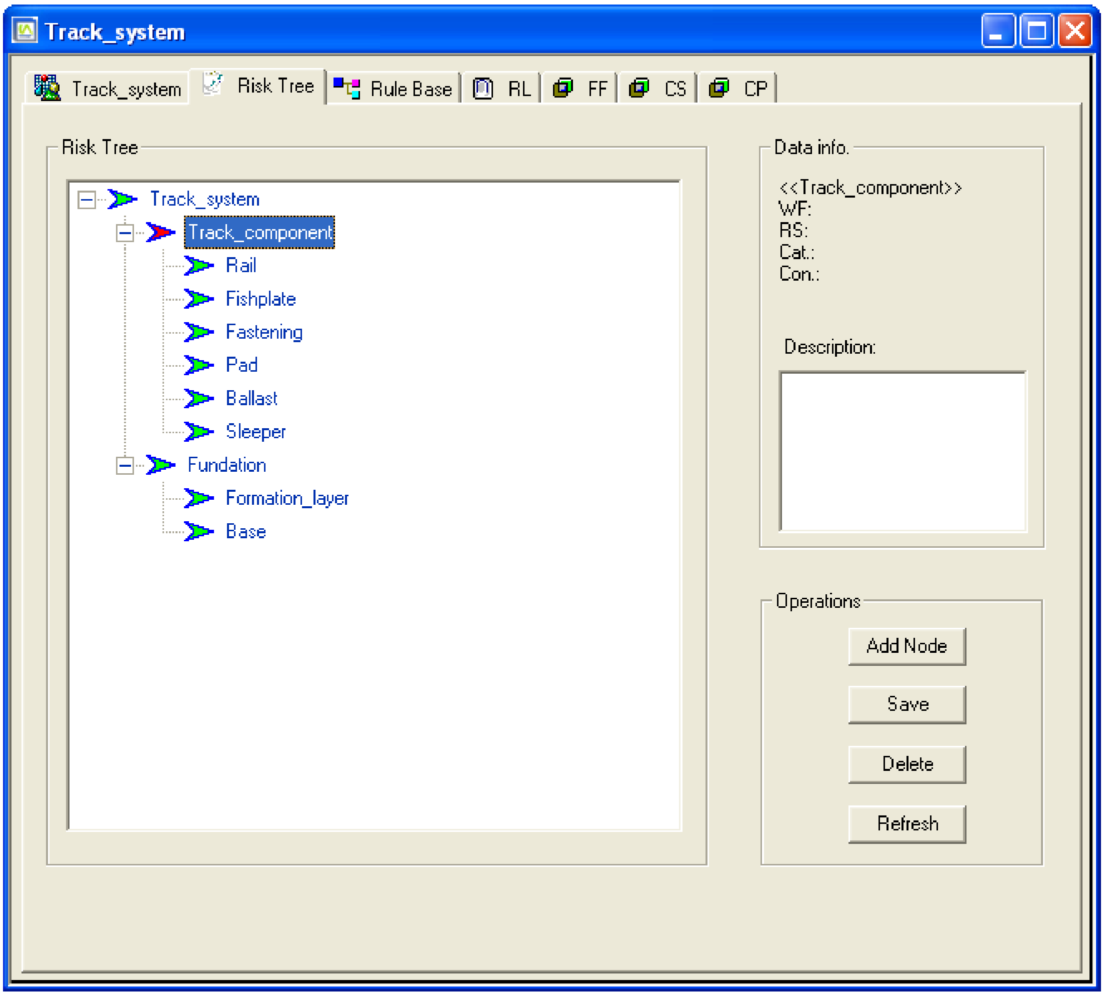
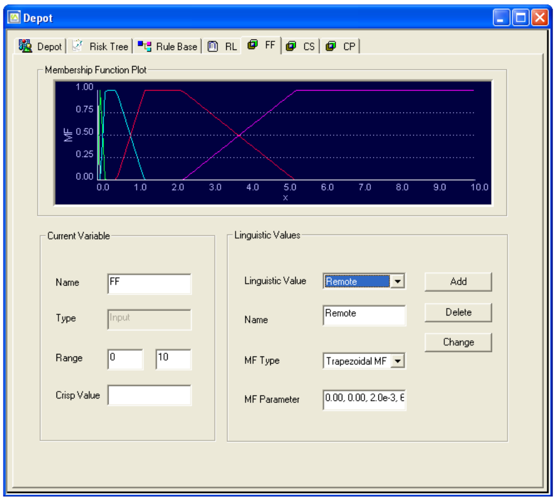


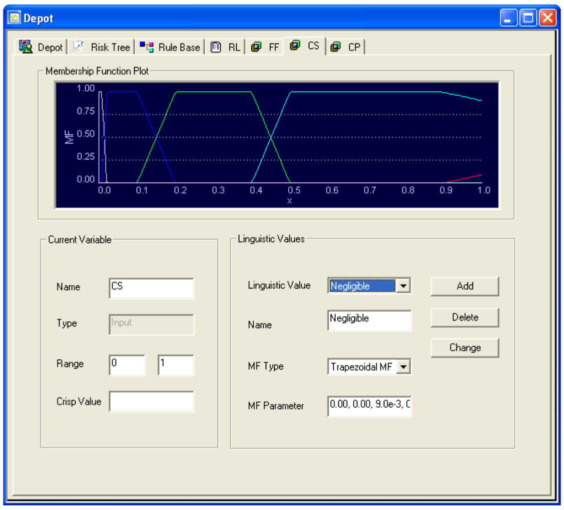
Figure 5-2 An example risk tree in RISRAS

5.3.2 Risk estimation

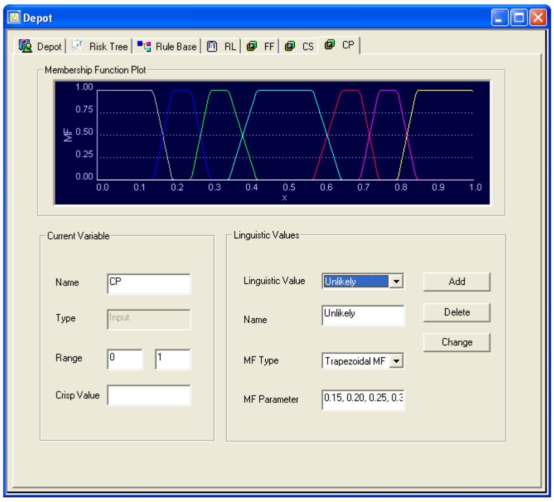
Risk estimation aims to assess the effects of failure events, i.e. RLs, in the railway system by taking FF, CP, CS and WF into consideration at component, subsystem and system level. The actual effect of the risk of a component failure is dependent on the values of FF, CP and CS. Traditionally, numerical values have been used to define the characteristics of identified risks, and statistical techniques have been applied to the analysis of the risk tree. After that, FRA is applied to perform the mathematical quantification of the linguistic variables to determine the RLs of failure events. In this case, input parameters FF, CP, CS and the output RL are defined using linguistic variables through RISRAS user interfaces as shown in Figure 5-3(a), (b) and (c). It should be noted that the numbers of linguistic variables used to describe these input parameters is flexible and depends on particular cases. Once the linguistic variables, MFs, and rule base have been established through the RISRAS user interface as shown in Figure 5-3(d), the system is ready to process FRA evaluation.



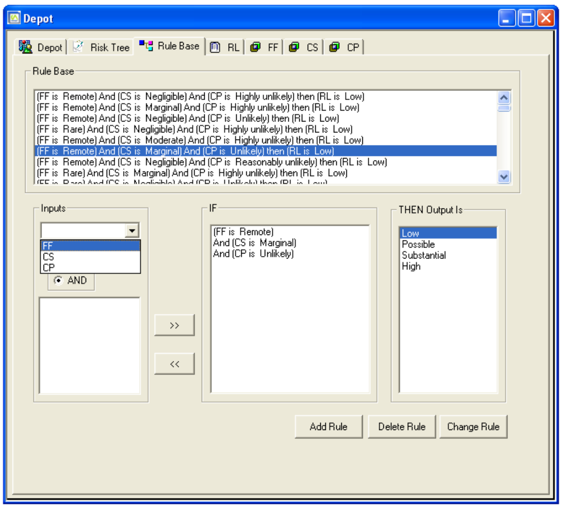
(a) FF



(b) CS



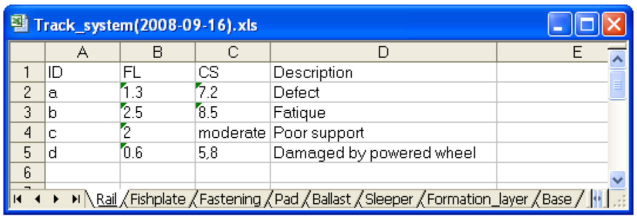
(c) CP



(d) rulebase

Figure 5-3 User interface for design of FF, CS, CP and rulebase

In many cases, there could be a large number of failure events involved at component level. The developed system provides an input template file to facilitate the risk assessment. The file is customised according to the risk tree determined during the risk identification. It has been developed from a Microsoft Excel file as shown in Figure 5-4, in which each spread sheet contains information of failure events identified for one component, including failure event ID (Identification), risk parameters (i.e. FF, CP and CS) and descriptions. The input values of risk parameters could be either linguistic terms, e.g. “rare”, “infrequent”, and “frequent”, or ranges, e.g. “between 0.01 and 0.03”, “between 0.1 and 0.4 most likely between 0.2 and 0.3 ”, or crisp values, e.g. “1” or “5e-3”. These input data will be restored in the database.


Track_system(2008-09-16).xls

	A	B	C	D	E
1	ID	FL	CS	Description	
2	a	1.3	7.2	Defect	
3	b	2.5	8.5	Fatique	
4	c	2	moderate	Poor support	
5	d	0.6	5,8	Damaged by powered wheel	
6					

Rail / Fishplate / Fastening / Pad / Ballast / Sleeper / Formation_layer / Base

Figure 5-4 Input template Excel file

Because the contribution of each failure event to the overall RL of a railway system is different, the weight of the contribution of each failure event should be taken into consideration in order to represent its relative contribution to the RL of a railway system. The application of Fuzzy-AHP has been employed in determining the relative importance of failure events in the decision making process so that risk assessment can be progressed from component level to subsystem level, and finally to a railway system level. In the developed RISRAS, the relevant importance has been taken into account by using Fuzzy-AHP analysis to quantify the expert judgements in order to obtain the WF of each component or subsystem. This can be done via user interface as shown in Figure 5-5 to develop an estimation scheme, which lists intensity of importance using qualitative descriptors. The purpose of the estimation scheme is to construct a pairwise comparison matrix. The developed system enables users to either input the values of the comparison matrix manually according the estimation scheme established or calculate these values on the basis of expert opinions through a “questionnaire”, as shown in Figure 5-7. Within the questionnaire, each spread sheet contains one expert’s judgements regarding the risk contributors compared in pairs.

Again, the format of the "questionnaire" could be linguistic terms, ranges or crisp values. Once the questionnaire is accomplished, a fuzzy-AHP comparison matrix will be produced based on the experts' judgements with their corresponding weights and then the WFs can be calculated by using a geometric mean technique as described in Section 4.2.2.3. It should be noted that if components are of equal importance to sub-systems that they belong to in some cases, it may not be necessary to perform a Fuzzy-AHP analysis. The developed system provides users with options of choosing risk analysis depending on the particular case either considering WFs or not considering WFs. The outcomes of risk estimation are represented as the risk degrees and the defined risk categories of RLs with a belief that a percentage will be used in the risk response phase.

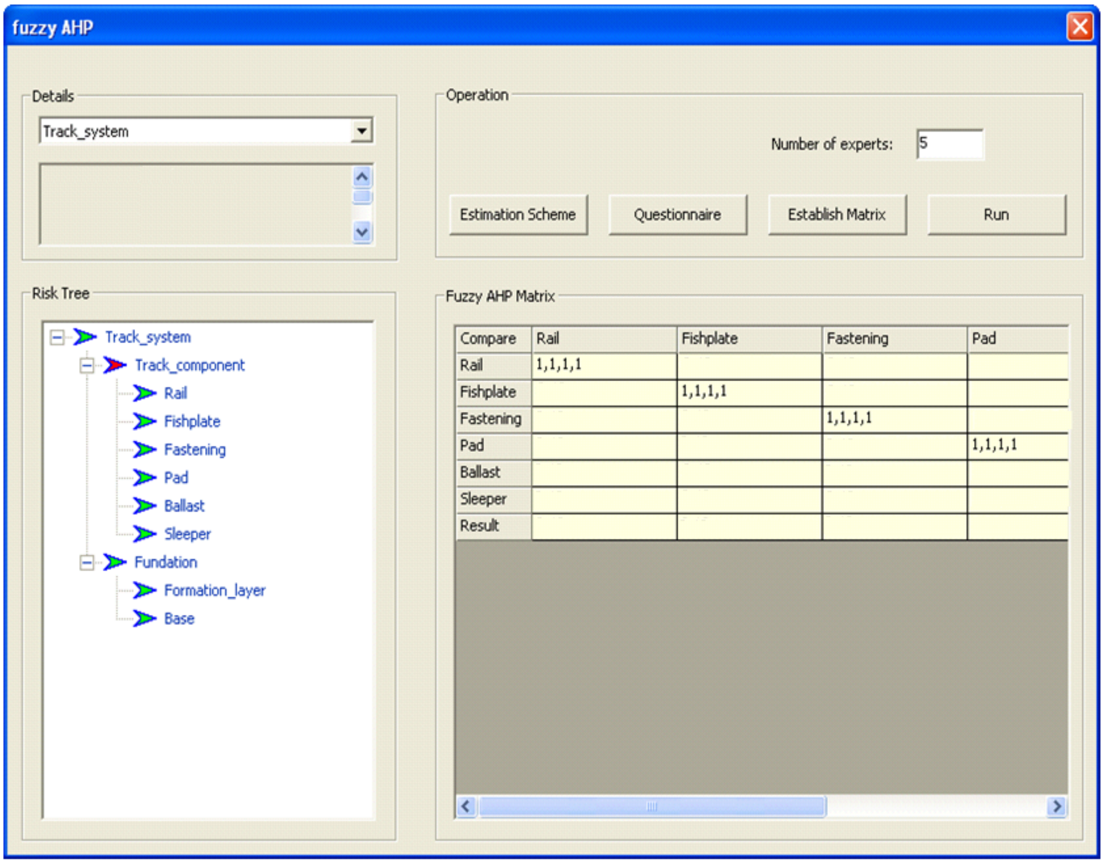


Figure 5-5 User interface for Fuzzy-AHP evaluation

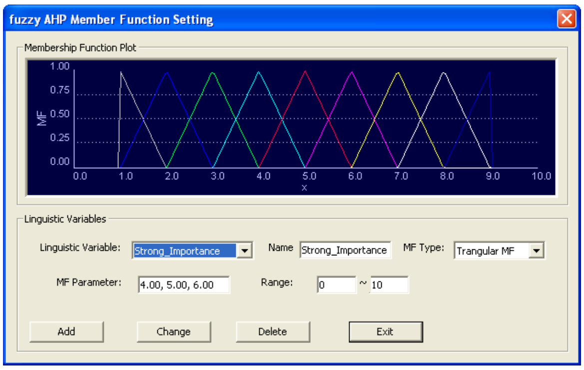


Figure 5-6 User interface for estimation scheme

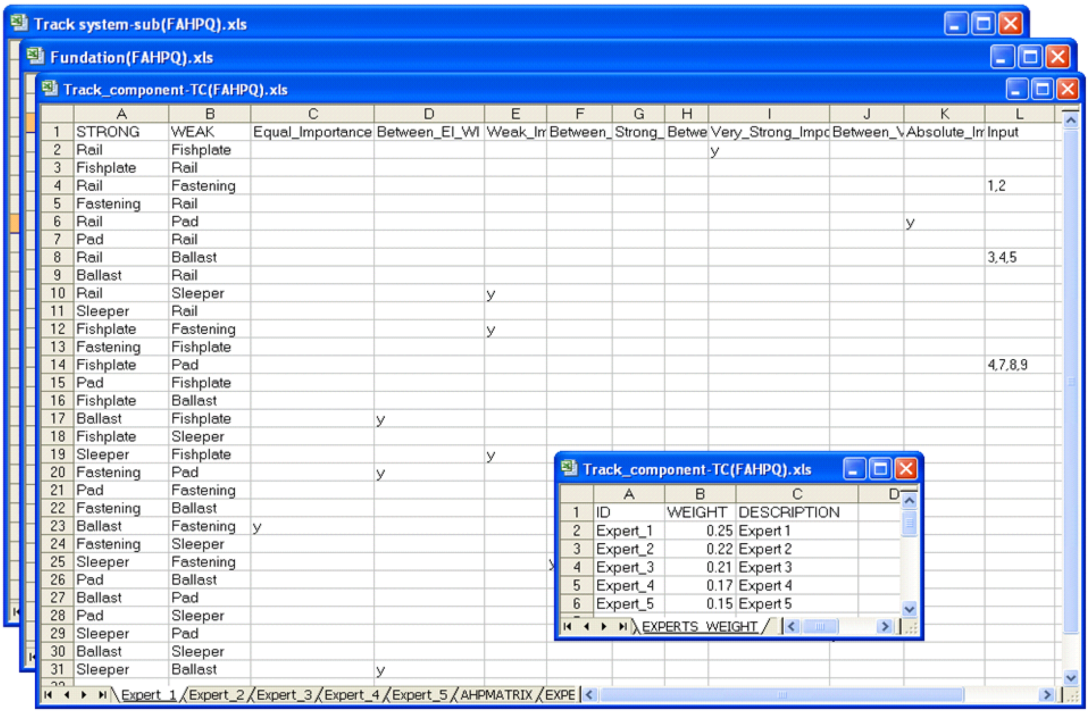


Figure 5-7 An example of an RISRAS Excel based questionnaire

5.3.3 Risk response

The results produced from the risk estimation may be used through the risk response phase. The results can be either viewed on the risk tree through the user interface as shown in Figure 5-7, or stored in a Microsoft Excel file as shown in Figure 5-9. The results can be used to assist risk analysts, engineers and managers in developing maintenance and operation policies. The results include risk contributions of components and subsystems to a railway system with risk scores as well as corresponding risk categories. In this study, the RLs are characterised into four regions, including ‘High’, ‘Substantial’, ‘Possible’ and ‘Low’. If risks are high, risk reduction measures must be applied or maintenance and operations have to be reconsidered to reduce the occurrence probabilities or to control the possible consequences. If risks are negligible, no actions are required but the information produced needs to be recorded for audit purposes. However, the acceptable and unacceptable regions are usually divided by a transition region. Risks that fall in this transition region need to be reduced to as low as reasonably practicable.

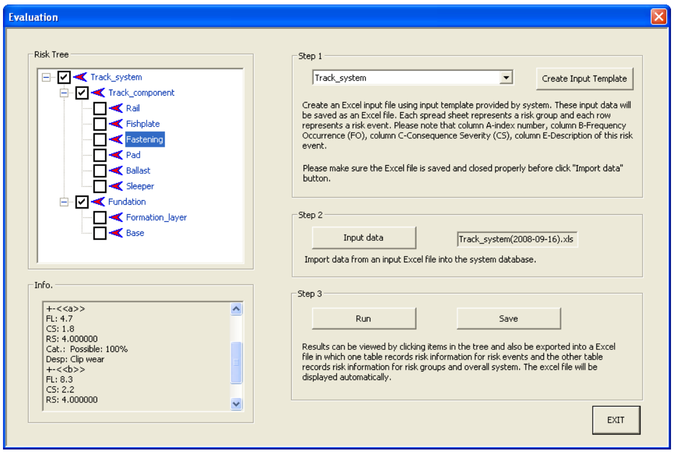


Figure 5-8 User interface for risk estimation

	A	B	C	D	E	F	G	H
1	ID	Item	Description	Parent_Item	FL	CS	Risk_Score	Risk_Category
2	1	a	Defect	Rail	1.3	7.2	4	Possible: 100%
3	2	b	Fatique	Rail	2.5	8.5	5.5	Possible: 50% Substantial: 50%
4	3	c	Poor support	Rail	2	moderate	4	Possible: 100%
5	4	d	Damaged by powered	Rail	0.6	5.8	4	Possible: 100%
6	5	a	Inadequately maintained rail joint support	Fishplate	2.8	4.7	4	Possible: 100%
7	6	a	Clip wear	Fastening	4.7	1.8	4	Possible: 100%
8	7	b	Screw loose	Fastening	8.3	2.2	4	Possible: 100%
9	8	a	Pad degradation	Pad	10.7	2.2	4	Possible: 100%
10	9	a	Performance	Ballast	0.7	5.5	4	Possible: 100%
11	10	a	Load damage	Sleeper	6.5	moderate	5.18	Possible: 82% Substantial: 18%
12	11	b	Maintenance damage	Sleeper	0.6	moderate	3.52	Possible: 100%
13	12	a	Load related failure	Formation_layer	0.07	4.5	4	Possible: 100%
14	13	b	Soil related failure	Formation_layer	0.02	moderate	3.58	Possible: 100%
15	14	c	Environment related	Formation_layer	0.04	6.8	4	Possible: 100%
16	15	a	Load related failure	Base	0.05	5.5	4	Possible: 100%
17	16	b	Soil related failure	Base	0.01	4.5	4	Possible: 100%
18	17	c	Evironment related	Base	0.02	6.9	4	Possible: 100%
19								

Track system Events / Track system Groups /

Figure 5-9 RISRAS output results in Excel file

5.4 Summary

This chapter describes the development of RISRAS, which provides a novel risk assessment tool for railway risk management. RISRAS is written in C++ running on a windows platform which has been developed on the basis of the proposed risk model, thus it can provide a systematic approach for users to assess risks from component level to sub-system level and finally to system level. The input data can be numerical numbers, fuzzy numbers, or even words. The application of Fuzzy-AHP in the assessment can solve the problems of risk information lost the risk assessment process. The output from the software can be shown on a risk tree or be exported into an excel file, which is convenient for users to view the results from risk analysis.

CHAPTER 6: RISK-BASED DECISION MAKING APPROACH

6.1 Introduction

Any constructed facility can be considered as an asset that needs to be maintained to ensure its optimal value over its life cycle (Hassanain et al., 2003). The aim of asset management is to achieve a desired outcome by maintaining and upgrading assets cost-effectively. In the railway industry, asset management is a costly task to ensure the network runs successfully while improving safety. According to statistics from the Department of Transport, in the period 2005-2009, an average of £5 billion has been invested each year into the railway industry for operating and maintaining the rail network (DfT, 2005). The challenge is how to use the limited investment while improving railway safety effectively and efficiently. Asset management, which usually involves maintenance work, is a vital part of railway duty holders, which should be included in their safety cases. A safety case covers all aspects of safety and specifies how the risks involved are to be minimised. A safety case also needs to include sufficient particulars to demonstrate that hazards with the potential to cause major accidents have been identified and evaluated, and that measures have been taken to reduce them to As Low As Reasonably Practicable (ALARP) (HSE, 2000). As stated earlier in this thesis, if risks are high, risk reduction measures must be applied or maintenance work has to be considered to reduce the occurrence probabilities or to control the possible consequences. If risks are negligible, no actions are required but the information produced needs to be recorded for audit purposes. However, the acceptable and unacceptable regions are usually divided by a transition region. Risks that fall in this transition region need to be reduced to ALARP. In the other words, “cost-effective” measures should be applied.

The literature review carried out by the researcher indicates that no formal risk based railway maintenance decision making support tools have been developed and applied to a stable environment in the railway industry, although some work has been conducted in this field. In order to show compliance with safety targets and to make maintenance and future investment decisions, a risk based railway maintenance decision-making support system for railway maintenance analysis using fuzzy reasoning approach (FRA), fuzzy analytical hierarchy process (fuzzy-AHP) and the TOPSIS method has been proposed.

The principal safety and maintenance issues in the railway infrastructure have been investigated and a risk model (Huang, et al, 2007; An et al, 2006 & 2007), a cost model and a risk-cost model have been developed for appraising maintenance schedules and also diagnosing risks. This provides an effective tool for getting a better understanding of the risks associated with railway systems and for making better maintenance decisions at the right time for managing the risks under various conditions. Currently, most of the asset management literature is aimed at fixed plant and usually focuses on improving business performance (HSL, 2005). TOPSIS (Hwang and Yoon, 1981) stands for technique for preference by similarity to the ideal solution, and is a multi-criteria decision making (MCDM) technique to aid selection in conditions of multiple criteria, which may solve the problem when cost and safety risk are taken into account in the decision making process. The proposed risk-based railway maintenance decision making system that combines the strengths of FRA and fuzzy-AHP techniques would tremendously aid the risk analysis process; especially in the maintenance process when significant decisions that affect the safety of railway systems are made. TOPSIS can be used to process a risk-cost model to obtain efficient maintenance strategies. This chapter presents a risk-cost model by using the TOPSIS method which synthesises the risk and cost models to produce the preference degree of each maintenance option. Once preference degrees of all maintenance options in hand are produced, the best option can be chosen. In this model, both the risk associated with a railway asset system and the costs incurred in each maintenance option are mapped onto a utility space and assessed in accordance with the respective constraints. Such a decision making model could be an effective method to get a better understanding of the risks associated with railway assets and to make better maintenance decisions at the right time for managing the risks under various conditions.

The chapter is structured as follows: after the introduction, Section 6.2 describes a risk based asset maintenance management framework. Sections 6.3 and 6.4 present a safety risk model and cost model, respectively. The TOPSIS method is introduced in Section 6.5. The proposed risk-cost model developed based on TOPSIS is presented in Section 6.6, which addresses both the risk associated with a railway asset assessed by a fuzzy risk assessment model and the costs incurred in each maintenance option. The preference degree of each maintenance option is calculated by using the TOPSIS method. Finally, a summary is given in Section 6.8.

6.2 A Risk Based Asset Maintenance Management Framework

The proposed risk-based asset maintenance management framework is shown in Figure 6-1, which consists of seven sequential processes: safety performance requirement, safety performance assessment, maintenance option design, ranking maintenance options, implementation, and asset performance review.

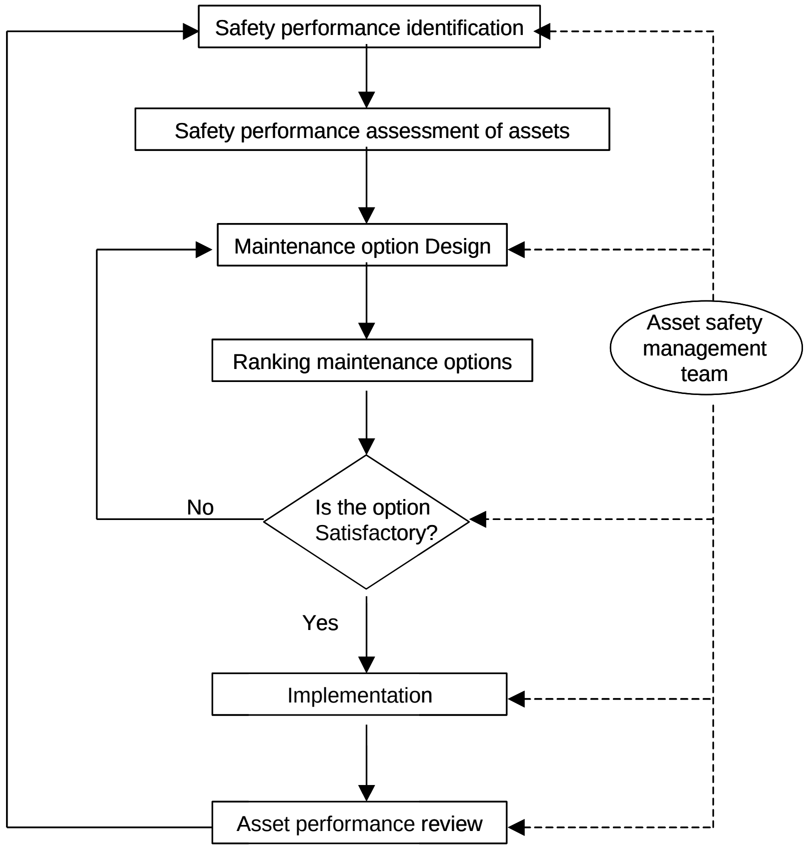


Figure 6-1 Railway asset maintenance management framework

The performance of a railway asset needs to be identified and justified by the asset safety management team. The needs for safety have to be specified, which should be done at different levels, e.g. component level, subsystem level and system level. The output of the identification of performance of a railway asset is a set of safety performance statements in which safety standards have been specified. The following typical items may need to be specified in the problem definition (An et al, 2006 & 2007; HSE, 2000 & 2005; Huang et al, 2005):

1. Sets of rules and regulations made by the national authorities and classification societies, e.g. Health & Safety Executive (HSE), Rail Safety and Standard Board (RSSB), London Underground Ltd (LUL), etc.
2. Deterministic requirements for safety, reliability, availability, maintainability, etc.
3. Criteria referring to the probability of occurrence of serious hazardous events and the possible consequences.

Maintenance option design is a process whereby decisions for maintenance works should be made on the basis of the results produced from the safety performance assessment. Usually, the asset safety management team can provide a number of maintenance options to choose from. The best option can be decided through a safety-cost analysis in ranking the maintenance options.

In ranking the maintenance option process, safety and cost need to be studied together to form a mathematical risk-cost model in order to attempt to maximise the safety benefits and to minimise the safety related cost of a railway asset. Safety and cost are two conflicting objectives, with higher safety leading to higher costs. This means that if the safety associated with a railway asset is improved, higher costs will usually be incurred. The cost incurred for safety improvement associated with a maintenance option is usually affected by many factors such as top event-caused cost, repair cost, and maintenance review cost. It is generally impossible to have a maintenance option that could maximise safety (i.e. minimise risks) and minimise cost such as the life cycle cost simultaneously. A compromise is therefore required. The decision as to which objective is to be stressed is dependent on the particular situation in hand. The appropriate level of safety then becomes dependent on the relative important of the two criteria. If the non-dominated maintenance options have to be obtained, it becomes feasible to use a MCDM technique to search for efficient or optimal maintenance options, where an efficient option is one in which the level of risk is the lowest with respect to a certain level of cost, or in which the level of cost is the lowest with respect to a certain level of risk. The safety associated with each maintenance option and the cost incurred in each maintenance option are then mapped onto the utility space and expressed in terms of the utility expressions such as "*slightly preferred*", "*moderately preferred*", "*preferred*" and "*greatly preferred*". Then the safety and cost estimates can be synthesised to obtain the preference estimation associated with the maintenance options. Obviously, the larger the preference degree is, the more desirable the maintenance option. Each preference degree of each maintenance option represents the comparison with others. The best maintenance option with the largest preference degree can be selected on the basis of the magnitudes of preference degrees. The detail of the proposed risk-cost model is described in the following sections.

Once the best maintenance option is selected, it should be implemented into maintenance work. Finally, a safety performance review can be conducted such as to review the practical experience gained and lessons learnt and consider possible ways of improving the safety management system.

6.3 Safety Risk Model

The occurrence of a railway system failure could cause serious consequences. The safety of a railway system can be improved by reducing the probability of the occurrence of system failure events. The occurrence of a system failure is completely dependent on the occurrence of the associated minimal failure events. If one failure event occurs, then system failure happens. Therefore, a reduction of the probability of occurrence of a system failure is a matter of reducing or eliminating the probabilities of occurrence of some significant failure events with relatively higher probabilities of occurrence, since it is impractical and impossible to reduce or eliminate all the associated failure events.

As mentioned earlier in Chapter 4, three parameters, failure frequency (FF), consequence probability (CP) and consequence severity (CS) of an event are usually used in railway safety risk analysis. The outcomes of safety risk assessment are represented in two formats, risk score and risk category with a belief of percentage, which provide very useful risk information to railway designers, operators, engineers and maintainers for making maintenance decisions. Details of the proposal safety risk model are described in Chapter 4, which is summarised as follows.

Suppose there are *n* identified subsystems of a railway asset system, the overall RL of a railway asset system can be defined by:

$$RL_{system} = \sum_{j=1}^{n} RL_j w_j \quad \text{E.q. 6-1}$$

where RL_{system} is the overall RL of a railway asset system, RL_j stands for the RL of the jth subsystem, and w_j is the WF of the jth subsystem. Similarly, assuming there are m components of the jth subsystem and each component has k failure modes, the RL of the jth subsystem and the ith are defined by:

$$RL_{subsystem,j} = \sum_{i=1}^{m} RL_{component,i} w_i \quad \text{E.q. 6-2}$$

$$RL_{component,i} = \sum_{t=1}^{k} FRA(FF_t, CP_t, CS_t) \quad \text{E.q. 6-3}$$

where FL_t , CP_t and CS_t are two input parameters of failure likelihood and consequence severity of the tth failure mode associated with the ith component.

The safety of the railway asset system can be improved by minimising the risks. If the reduction or elimination of one failure mode does not significantly affect others, the risk function can be expressed as the sum of the probabilities of occurrence of the system failure events and k failure modes considered for reduction or elimination while each system failure event is weighted on the basis of the severity of its possible consequences. The safety risk model can be defined by:

Min: $$RL_{system} = \sum_{j=1}^{n} RL_j w_j \quad \text{E.q. 6-4}$$

Subject to: $RL_{system,\min} \leq RL_{system} \leq RL_{system,\max}$

$$RL_{subsystem,\min} \leq RL_{subsystem,j} = \sum_{i=1}^{m} RL_{component,i} \leq RL_{subsystem,\max}$$

$$RL_{component,\min} \leq RL_{component,i} = \sum_{t=1}^{k} FRA(FF_t, CP_t, CS_t) \leq RL_{component,\max}$$

6.4 Cost Model

Cost is always an important issue in the railway maintenance work process. The safety-related life cycle cost of a railway system may be modelled by taking into consideration the top failure event caused consequences, repair/renewal cost, maintenance cost and performance review cost. The following simplifying assumptions are made to implement cost modelling:

- The basic diagram of the system to be analysed is not changed.
- Manpower and spare parts are sufficient for repairs and maintenance activities.
- All the systems return to their original conditions after full maintenance.
- Failed components/subsystems are repaired "same as new" and other components/subsystems are not affected by the repairs.
- Cost incurred is expressed as the present value.

A railway system may have several serious top failure events such as derailment, fire and explosion, each of which could result in a system breakdown and possibly cause serious consequences such as injury or death, damage or loss of property and damage of the environment. Therefore, the top failure event caused cost includes costs directly caused by the occurrence of the railway system top failure events, lost income due to the system being not in normal service, and repair costs caused by the occurrence of the railway system top failure events. Maintenance cost covers cost of labour, cost of parts and lost income during periods of maintenance activities. If a major component/subsystem in a railway system fails, the system should be shut down and the failed component/subsystem should be replaced or repaired immediately. Repair/renew cost includes cost of labour, cost of parts and lost income due to the system being not in normal service because of failures of the components/subsystems. Since the basic diagram of the system is not changed, a performance review may only involve the use of more reliable components or subsystems to reduce or eliminate the most significant failure modes associated with the identified system top failure events. Obviously, the more investment that is directed at the system for safety improvement, the higher the safety level of system, which results in lower probabilities of occurrence of railway system top failure events leading to less expenditure in the operation and maintenance process. The performance review cost therefore includes the cost of labour, cost of parts and lost income during the periods of maintenance activities associated with the *t*th failure mode of the *i*th component/the *j*th subsystem failure event. Let *Cost* represent the safety-related cost function. The cost model can be defined by:

Min: $$Cost = Cost_T(X) + Cost_R(X) + Cost_M(X) + Cost_P(X,Y) \qquad \text{E.q. 6-5}$$

Subject to: $Cost_{\max} \geq Cost \geq Cost_{\min}$

where *Cost* is the total cost, $Cost_T$ is the cost caused top failure event of a railway system, $Cost_R$ is repair/renew cost, $Cost_M$ is maintenance cost, $Cost_P$ is performance review cost after the repair/renew or maintenance works, X stands for the variables of costs caused by a system top failure event, maintenance cost, repair/renewal cost and maintenance cost, and Y stands for system performance review cost after the repair/renewal and maintenance work.

The first three terms of the cost model deal with the maintenance policies and the last term takes into account both the maintenance polices and performance review actions. This model implies that the maintenance policies and the performance review actions should be implemented to minimise the safety-related cost.

6.5 TOPSIS Methodology

The TOPSIS stands for technique for preference by similarity to the ideal solution, which was initially introduced by Hwang and Yoon in 1981. It is a multiple criteria method for identifying solutions from a finite set of alternatives. The basic principle is that the choice of alternative should have the shortest distance from the positive ideal solution to the farthest distance from the negative ideal solution (Abo-Sinna & Amer, 2005; Shih, Shyur, & Stanley Lee, 2007). A relative advantage of TOPSIS is the ability to quickly identify the best alternative (Parkan and Wu, 1997). Currently, it has been adapted into a number of applications, such as in financial investment, manufacturing processes, etc (Agrawal et al., 1991; Chau and Parkan, 1995). The procedure of TOPSIS can be described in 6 steps (Jahanshahloo et al., 2006; Olson, 2004; Yang & Hung, 2007):

Step 1: Calculate the normalised decision matrix. The normalised value of the *i*-th alternative under the *j*-th criterion $x_{i,j}$ is calculated as

$$x_{i,j} = \frac{a_{i,j}}{\sqrt{\sum_{i=1}^{m} a_{i,j}^{\ 2}}}, i = 1,2,..., m, j = 1,2,..., n. \qquad \text{E.q. 6-6}$$

where $a_{i,j}$ is the original value of the *i*-th alternative under the *j*-th criterion.

Step 2: Calculate the weighted normalised decision matrix. The weighted normalised value of the *i*-th alternative under the *j*-th criterion $y_{i,j}$ is calculated as

$$y_{i,j} = w_j \cdot x_{i,j}, i = 1,2,..., m, j = 1,2,..., n \qquad \text{E.q. 6-7}$$

Where w_j is the weight of the *j*-th criterion and $\sum_{j=n}^{n} w_j = 1$.

Step 3: Determine the positive ideal solution A^+ and negative ideal solution A^-

$$A^+ = \{y_1^+, y_2^+,..., y_j^+,..., y_n^+\} \qquad \text{E.q. 6-8}$$

$$A^- = \{y_1^-, y_2^-,..., y_j^-,..., y_n^-\} \qquad \text{E.q. 6-9}$$

Where y_j^+ and y_j^- are positive ideal and negative ideal value under the *j*-th criterion.

Step 4: Calculate the separation measures, using the n-dimensional Euclidean distance. The separation of each alternative from the positive ideal solution is given as

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{i,j} - y_j^+\right)^2}, i = 1,2,..., m. \qquad \text{E.q. 6-10}$$

Similarly, the separation from the negative ideal solution is given as

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{i,j} - y_j^-\right)^2}, i = 1,2,..., m. \qquad \text{E.q. 6-11}$$

Step 5: Calculate the relative closeness to the ideal solution. The relative closeness of the alternative A_i with respect to A^+ is defined as

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, i = 1,2,..., m \qquad \text{E.q. 6-12}$$

Since $D_i^+ \geq 0$ and $D_i^- \geq 0$, then, clearly, $C_i \in [0,1]$

Step 6: Rank the preference order. The basic principle of the TOPSIS method is that the chosen alternative should have the ‘‘shortest distance” from the positive ideal solution and the ‘‘farthest distance” from the negative ideal solution.

6.6 Risk-Cost Model

Facing various maintenance options, railway engineers, managers and risk analysts are often confronted with conflicting objectives, i.e. minimising cost and maximising safety performance, in other words, minimising risk. A risk-cost model is proposed based on the TOPSIS method which combines the safety model with the cost model to calculate the preference degree of maintenance options.

For example, if just maintenance cost should be taken into consideration in the cost model, the cost model is simplified as:

Min: $$Cost_i = Cost_L(A_i) + Cost_M(A_i) + Cost_E(A_i) + Cost_O(A_i) \quad \text{E.q. 6-13}$$

The risk model is defined by:

Min: $$RL_i = RL_{system}(A_i) \quad \text{E.q. 6-14}$$

where $Cost_i$ is the total cost associated with the *i*-th maintenance option (A_i), $Cost_L$ is the labour cost, $Cost_M$ is the cost of materials and parts, $Cost_E$ is the cost caused by using equipment and $Cost_O$ stands for other costs, such as loss of income in the period of the maintenance activities, fuel cost, review cost and management cost; RL_i is the total system risk level after the *i*-th maintenance option (A_i).

However, all maintenance options must satisfy constraints in relation to safety requirements set up by national authorities and classification societies, e.g. Health & Safety Executive, Rail Safety and Standard Board, London Underground Ltd etc. The objective of the cost model is to minimise the maintenance cost. At some point, some constraints should be satisfied, for example the limited maintenance budget. Thus, finite maintenance options are always available in practice.

Subject to: $A_i \in \{A_1, A_2, ..., A_m\}$ E.q. 6-15

As described earlier in this chapter, cost and risk are two competing objectives. The purpose of the development of a risk-based maintenance decision making model is to evolve a compromise for maintenance solutions by balancing and effectively utilising resources so that these two objectives can be simultaneously attained as closely as possible. Figure 6-2 shows the relationship between risk and cost. As can be seen, the more investment is put into at the system for safety improvement, the higher the safety level of system can be received, which results in lower probabilities of occurrence of railway system top failure events and also leads to less expenditure in the operation and maintenance process. However, with the cost increasing rapidly, risk reduction decreases in contrast. In this situation, cost-effective principles should be applied, i.e. ALARP. Therefore, the optimal operation and maintenance solution should be selected to minimise the risks and improve the safety of the system and simultaneously minimise the cost.

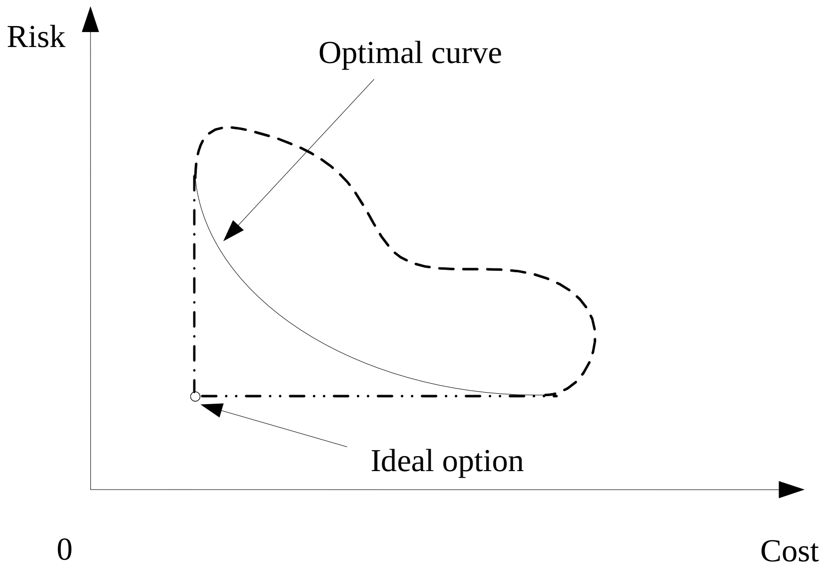


Figure 6-2 Risk vs Cost

The proposed risk-cost model based on TOPSIS is shown in Figure 6-3. In accordance with the results of risk assessment, various possible maintenance options may be designed for selection. Each option regarding risk and cost information should be collected and analysed by using the safety risk model and cost model, respectively, in order to assess the corresponding risk reduction and cost estimation.

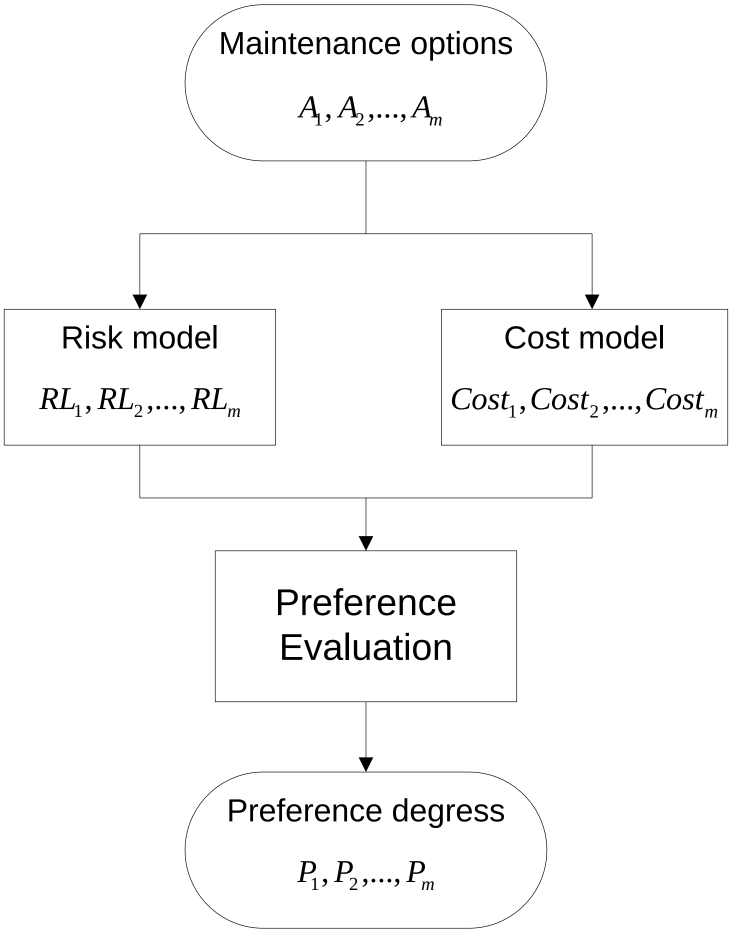


Figure 6-3 An overview of the process of maintenance option selection

Then, preference evaluation should be applied to produce the preference degree of each maintenance option. According to the TOPSIS method, the procedure of preference evaluation can be described as the following steps:

Step 1: calculate normalised cost and risk value respectively. The normalised cost $x_{i,\cos t}$ and risk $x_{i,RL}$ values of the *i*-th maintenance option are calculated as

$$x_{i,\cos t} = \frac{Cost_i}{\sqrt{\sum_{i=1}^{m} Cost_i^{\ 2}}}, i = 1,2,..., m. \quad \text{E.q. 6-16}$$

$$x_{i,RL} = \frac{RL_i}{\sqrt{\sum_{i=1}^{m} RL_i^{\ 2}}}, i = 1,2,..., m. \qquad \text{E.q. 6-17}$$

Where $Cost_i$ and RL_i are the values derived from the cost model and the risk model respectively, and associated with the *i*th maintenance option.

Step 2: Calculate the weight normalised cost and risk value respectively. The weighted normalised cost $y_{i,\cos t}$ and risk $y_{i,RL}$ values of the *i*-th maintenance option are calculated as

$$y_{i,\cos t} = w_{\cos t} \cdot x_{i,\cos t}, i = 1,2,..., m. \qquad \text{E.q. 6-18}$$

$$y_{i,RL} = w_{RL} \cdot x_{i,RL}, i = 1,2,..., m. \qquad \text{E.q. 6-19}$$

where $w_{\cos t}$ and w_{RL} are the weights of cost and risk criterion. In the case, if risk and cost are equal importance, then $w_{\cos t} = w_{RL} = 0.5$.

Step 3: Determine the best A^+ and worst A^- scenario options based on those weighted normalised cost and risk values.

$$A^+ = \left\{ y^+_{\cos t}, y^+_{RL} \right\} = \left\{ \bigcap_{i=1}^{m} y_{i,\cos t}, \bigcap_{i=1}^{m} y_{i,RL} \right\} \qquad \text{E.q. 6-20}$$

$$A^- = \left\{ y^-_{\cos t}, y^-_{RL} \right\} = \left\{ \bigcup_{i=1}^{m} y_{i,\cos t}, \bigcup_{i=1}^{m} y_{i,RL} \right\} \qquad \text{E.q. 6-21}$$

Step 4: Calculate the separation distances. The separation of the *i*-th maintenance option from the best scenario option D_i^+ is given as

$$D_i^+ = \sqrt{\left(y_{i,\cos t} - y_{\cos t}^+\right)^2 + \left(y_{i,RL} - y_{RL}^+\right)^2}, i = 1,2,..., m. \quad \text{E.q. 6-22}$$

Similarly, the separation of the *i*-th maintenance option from the worst scenario option D_i^- is given as

$$D_i^- = \sqrt{\left(y_{i,\cos t} - y_{\cos t}^-\right)^2 + \left(y_{i,RL} - y_{RL}^-\right)^2}, i = 1,2,..., m. \quad \text{E.q. 6-23}$$

Step 5: Calculate the preference degree based on those separations. The preference degree of the *i*-th maintenance option P_i is calculated as

$$P_i = \frac{D_i^-}{D_i^+ + D_i^-}, i = 1,2,..., m \quad \text{E.q. 6-24}$$

Step 6: Rank the maintenance options based on preference degrees in decreasing order.

Obviously, the larger the preference degree is, the more desirable the maintenance option. Each preference degree of each maintenance option represents its comparison with others. Once all preference degrees of all maintenance options in hand are produced, the best maintenance option can be selected, which has the largest preference degree.

6.7 Summary

This chapter presents a risk-based maintenance decision making model by using the TOPSIS method, which incorporates safety risk and cost into the railway maintenance process to make maintenance decisions for railway systems. The proposed risk-based maintenance decision making model provides railway engineers, operators, managers and maintainers with a useful method and tool to make full use of the information produced in a safety risk and cost analysis and to take into consideration maintenance aspects simultaneously. A case study to demonstrate the application of the proposed risk based maintenance decision making model is presented in Chapter 8.

CHAPTER 7: CASE STUDY ON RISK ASSESSMENT OF SHUNTING AT HAMMERSMITH DEPOT

7.1 Introduction

In this chapter, an illustrated case example on risk assessment of shunting at Hammersmith depot is used to demonstrate the proposed risk assessment methodology. The case materials have been collected from industry (Metronet, 2005). The input parameters are FF, CP and CS of hazardous events. The outputs of risk assessment are RLs of hazardous events, hazard groups, and the overall RL of shunting at Hammersmith depot with risk scores located from 0 to 10 and risk categorised as ‘Low’, ‘Possible’, ‘Substantial’ and ‘High’ with a percentage belief. In the FRA risk estimation phase, the RLs of hazard groups are calculated using the FRA based on the aggregation results of each hazardous event belonging to the particular hazard group. In the Fuzzy-AHP estimation phase, the overall RL of shunting at Hammersmith depot is obtained on the basis of the aggregation of the RLs of each hazard group contribution weighted by using fuzzy-AHP method.

7.2 Hazard Risk Identification at Hammersmith Depot

Hammersmith depot is one of the largest depots in London Underground. Historical data of accidents and incidents have been recorded over the past ten years. In this case, the historical accident and incident databases have been reviewed in Hammersmith depot. Seven hazard groups and 17 sub-hazard groups have been identified and defined, and each sub-hazard group consists of a number of hazardous events (Metronet, 2005), which are described as follows:

1) The derailment hazard group (DHG) includes two sub-hazard groups i.e. typical outcome (minor injury) and worst-case scenario (major injury), which have been identified based on the previous accidents and incidents. Like Waterloo depot, here derailment scenarios are not considered to infringe other running lines. Due to low speed and configuration of the track, the most likely scenario is that the train will drop off the track, injuring only the driver. Both sub-hazard groups consist of six hazardous events such as: track related faults, including mechanical failure of track e.g. broken rail and fishplates; signalling related faults, including mechanical failure of signals and points; rolling stock faults, including mechanical failure of rolling stock e.g. brakes, axles and bogies; structure failure including collapsed drain or civil structure beneath the track leading to derailment; object from train including object falls from train (e.g. motor) leading to derailment (like the Chancery Lane incident); and human errors, including human error causing derailment e.g. overspending, incorrect routing.

2) The collision hazard group (CHG) consists of four sub-hazard groups i.e. collision between trains in a worst case scenario (fatality), collision between trains with a typical outcome (multiple minor injuries), collision hazard of worst case scenario (fatality) and collision hazard of typical outcome (minor injury). Collision between trains involves three scenarios. For example, when MR train is moving out over infrastructure from OZ18, LU train is moving out from platform 3 due to train or signal failure. Collision hazards include two hazardous events, for example, collision with an object on the track, collision with a terminal e.g. over running into a buffer stop on road 24 due to excessive speed, brake failure or human error.

3) The train fire hazard group (TfHG) only has one sub-hazard group, i.e. train fire typical outcome, which covers minor injury, as it is believed that a train would not catch fire fast enough to endanger a driver more than through smoke inhalation. There are two hazardous events which could result in the train fire, including arcing from the conductor rail causing a train fire, and electrical, oil or hydraulic failure leading to train fire.

4) The electrocution hazard group (EHG) has two sub-hazard groups, typical outcome (fatality) and best case scenario (major injury), which cover a number of hazardous events, for example, contact with the conductor rail whilst entering/leaving the cab, contact with the conductor rail whilst walking to the train and plugging in gap jumper leads if the train has stalled/gapped. Due to the high voltage direct current, fatality is the most likely consequence. Even if the injury is not fatal, it will still be serious.

5) The slips/trips hazard group (SHG) includes three sub-hazard groups, i.e. minor injury, major injury and fatality. The hazardous events include, for example, instances when MR shunter is required to leave the train, risks to a ground shunter and instances when a person is required to approach a train when it is stalled/gapped. Slips / trips are acknowledged as high frequency, low consequence events. The majority of slips and trips are agreed as minor injuries; fatalities are very unlikely. There is a chance of broken bones if a person slips or trips badly.

6) The falls from height hazard group (FHG) consists of three sub-hazard groups, i.e. minor injury, major injury and fatality which cover falls from height such as when a shunter leaves the train cab. A fall from height is much more likely than a slip / trip to result in major injury.

7) The train strikes person hazard group (TsHG) has been identified based on the record in the past 10 years into two sub-hazard groups – major injury and fatality. The hazardous events in these two sub-hazard groups include a train striking an authorized person, including other depot workers (e.g. ground shunter) or track side staff, and a train striking an unauthorized person, e.g. trespassers etc. A side swipe collision is considered non-fatal but still serious. Collision head-on is considered fatal.

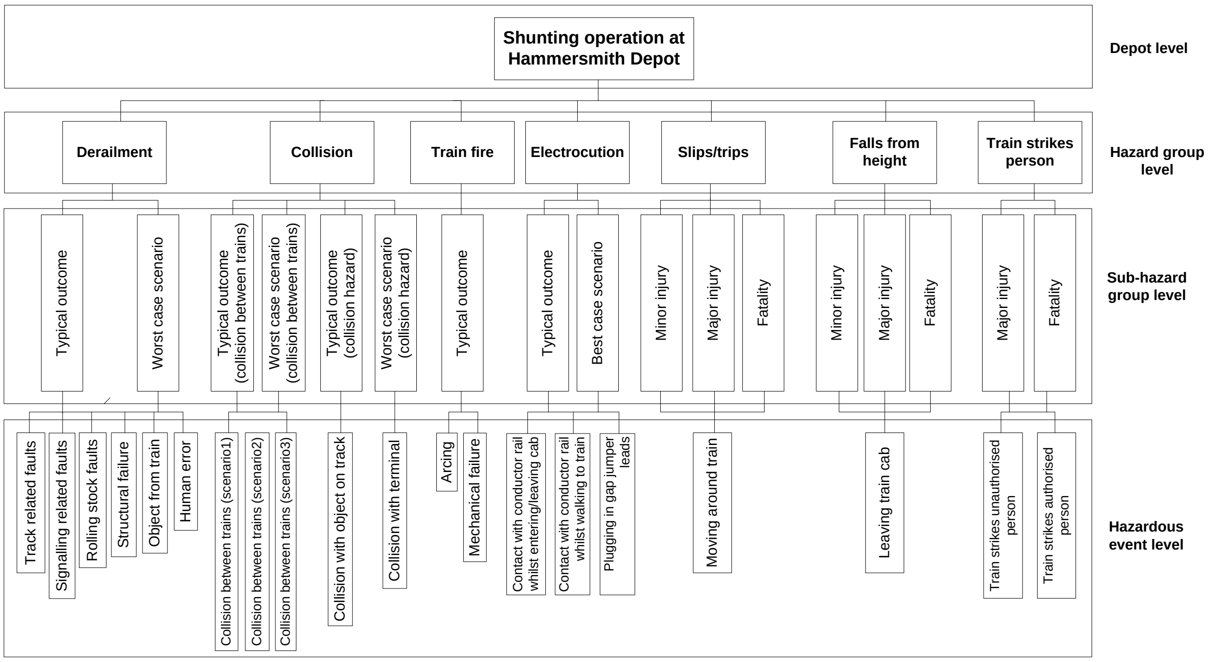


Figure 7-1 Hazard identification at different levels for Hammersmith depot

As described in Section 4.2.2.1, a risk tree has been developed for risk analysis of shunting at Hammersmith depot, as shown in Figure 7-1. Risk assessment is initially carried out from hazardous events and then progressed up to sub-hazard group level, hazard group level and finally to depot level. The qualitative descriptors of FF, CS, CP and RL have been developed for the analysis of shunting at Hammersmith depot and the FRA is employed to estimate the RL of each hazardous event in terms of FF, CS and CP. The definition of FF defines the number of times an event occurs over a specified period, e.g. number of events/year. The qualitative descriptors of FF are defined as “Remote”, “Rare”, “Infrequent”, “Occasional”, “Frequent”, “Regular” and “Common” and their meanings are presented in Table 7-1.

Rank	**Qualitative descriptors**	**Description**	**Approximate numerical value (event/yr)**	**Parameters of MFs (trapezoid)**
1	Remote	< 1 in 175 years	0.002	0, 0, 2E-3, 6E-3
2	Rare	1 in 35 years to 1 in 175 years	0.01	2E-3, 6E-3, 1.5E-2, 4E-2
3	Infrequent	1 in 7 years to 1 in 35 years	0.05	1.5E-2, 4E-2, 8E-2, 2E-1
4	Occasional	1 in 1 ¼ years to 1 in 7 years	0.25	8E-2, 2E-1, 5E-1, 1.25
5	Frequent	1 in 3 months to 1 in 1 ¼ years	1.25	5E-1, 1.25, 2.25, 5.25
6	Regular	1 in 20 days to 1 in 3 months	6.25	2.25, 5.25, 10.25, 31.25
7	Common	1 in 4 days to 1 in 20 days	31.25	10.25, 31.25, 100, 100

Table 7-1 Definitions of qualitative descriptors of FF

CS describes the magnitude of the possible consequence in terms of the number of fatalities, major and minor injuries resulting from the occurrence of a particular hazardous event. The qualitative descriptors of CS are defined as “Negligible”, “Marginal”, “Moderate”, “Critical”, and “Catastrophic” and their meanings are shown in Table 7-2, where major and minor injuries are calculated in terms of equivalent fatalities. Ten major injuries or 200 minor injuries are considered equal to one equivalent fatality (TLL, 2004; Metronet, 2005). For example, qualitative descriptor ‘Marginal’ is defined to describe the consequence level of minor injury with an approximate numerical value of 0.005.

Rank	Qualitative descriptors	Description	Numerical value (event/yr)	Parameters of MFs (trapezoid)
1	Negligible	No injury and/or negligible damage to the system	0–0.1	0, 0, 9E-3, 2E-2
2	Marginal	Minor system damage and/or minor injury	0.1–2	9E-3, 2E-2, 1E-1, 2E-2
3	Moderate	Failure causes some operational dissatisfaction and/or major injury	2–5	1E-1, 2E-1, 4E-1, 5E-1
4	Critical	Major system damage and/or severe injury	5–10	4E-1, 5E-1, 9E-1, 2
5	Catastrophic	System loss and/or fatality	>10	9E-1, 2, 5, 5

Table 7-2 Definitions of qualitative descriptors of CS

CP defines the FF that failure effects that will happen given the occurrence of the failure. One may often use such qualitative descriptors as “Highly unlikely”, “Unlikely”, “Reasonably unlikely”, “Likely”, “Reasonably likely”, “Highly likely” and “Definite”. Table 7-3 shows the evaluation criteria of CP and the corresponding qualitative descriptors.

Rank	Qualitative descriptors	Description	Parameters of MFs (trapezoid)
1	Highly unlikely	The occurrence likelihood of accident is highly unlikely.	0.00, 0.00, 0.15, 0.20
2	Unlikely	The occurrence likelihood of accident is unlikely but possible given the occurrence of the failure event.	0.15, 0.20, 0.25, 0.30
3	Reasonably unlikely	The occurrence likelihood of accident is between likely and unlikely.	0.25, 0.30, 0.35, 0.425
4	Likely	The occurrence likelihood of accident is likely.	0.35, 0.425, 0.575,0. 65
5	Reasonably likely	The occurrence likelihood of accident is between likely and highly likely.	0.575, 0.65, 0.70, 0.75
6	Highly likely	The occurrence likelihood of accident is very likely	0.70, 0.75, 0.80, 0.85
7	Definite	The accident occurs given the occurrence of the failure event.	0.80, 0.85, 1.00, 1.00

Table 7-3 Definitions of qualitative descriptors of CP

The qualitative descriptors of RL are defined as “Low”, “Possible”, “Substantial”, and “High”.

Their definitions, which are generally similar to those described in EN50126, EN50129, and GE/GN8561 (Railway Safety, 2002), are listed in Table 7-4. The risk score is defined in a manner that the lowest score is 0, whereas the highest score is 10. For example, qualitative descriptor, 'Low', is defined on the basis of the risk score ranging from 0 to 2. Similar to the input qualitative descriptors of FF, CS and CP, the trapezoidal MFs are used to describe the RL. The results of RLs can be expressed either as a risk score located in the range from 0 to 10 or as risk category with a belief of percentage.

Rank	**Qualitative descriptors**	**Description**	**Parameters of MFs (trapezoid)**
1	Low	Risk is acceptable	0, 0, 1, 2
2	Possible	Risk is tolerable but should be further reduced if it is cost-effective to do so	1, 2, 4, 5
3	Substantial	Risk must be reduced if it is reasonably practicable to do so	4, 5, 7, 8
4	High	Risk must be reduced to safe in exceptional circumstances	7, 8, 10, 10

Table 7-4 Definitions of qualitative descriptors of RL

Because three parameters, FF, CP, and CS are used to determine the RLs of hazardous events, the rule base consists of 245 if-then rules for this study. Figure 7-2 shows five rule matrices. It can be seen that each matrix consists of 49 rules with a particular qualitative descriptor of CS. For example, the rule at the top left of the matrix of CS = Negligible would be expressed as follows:

IF FF is *Remote* and CP is *Highly unlikely* and CS is *Negligible*, THEN RL is *Low*.

The RISRAS provides the user with a design panel as described in Section 5.3.2 to develop the rule bases, which enables the user to easily update or modify rules depending on particular cases.

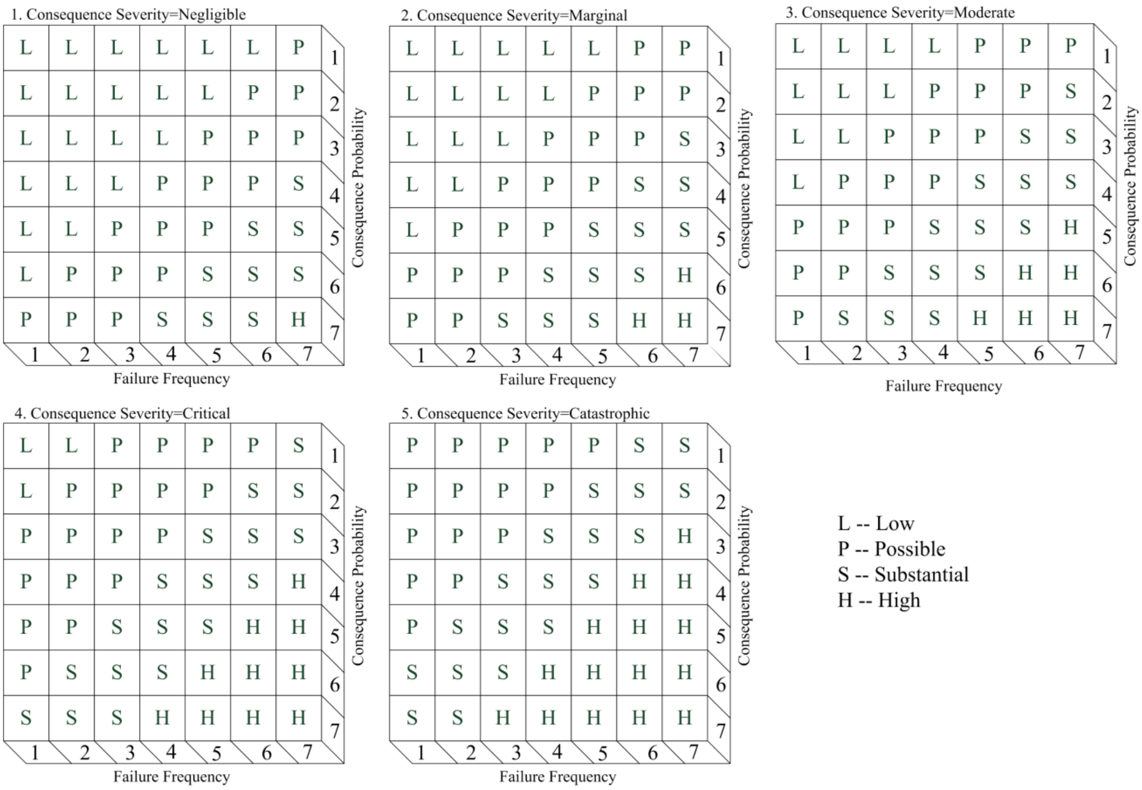


Figure 7-2 Fuzzy rule base matrices

In this case, five experts with high qualifications regarding this subject are involved in the risk assessment group. EIs are allocated to experts by E.q. 4-1 on the basis of their background and experience as shown in Table 7-5. For example, expert E5 has less experience, therefore he has the lowest EI =0.16.

Experts	**Yeare of Experience**	**EIs**
E1	10 years experience	0.21
E2	10 years experience	0.24
E3	10 years experience	0.21
E4	8 years experience	0.18
E5	5 years experience	0.16

Table 7-5 EIs for five experts

7.3 FRA Risk Estimation

As the data of FF, CP and CS in this case are directly related to sub-hazard group, the assessment is carried out from sub-hazard group level, then up to hazard group level and finally to depot level. The risk data of sub-hazard groups are then processed following the procedures described in Section 4. 2.3.

Step 1: Input FFs, CSs, and CPs.

As the data obtained are in numerical format, these crisp values of FF, CP and CS of sub-hazard groups are directly inputted into the RISRAS through the input template file. For example, the FF, CP and CS of the sub-hazard group "derailment (typical outcome)" are '3.33E-2', '99%', and '0.005' respectively, as shown in Table 7-9.

Step 2: Convert inputs into UFNs.

These crisp values are converted into corresponding UFNs according to Table 4-1. The converted UFNs A_{FF}, A_{CP} and A_{CS} of the FF, CP and CS of the sub-hazard group "derailment (typical outcome)" are:

$$A_{FF} = \{3.33E-2, 3.33E-2, 3.33E-2, 3.33E-2\}$$
$$A_{CP} = \{0.99, 0.99, 0.99, 0.99\}$$
$$A_{CS} = \{0.005, 0.005, 0.005, 0.005\}$$

Step 3: Aggregate UFNs.

As the data are obtained from the historical record, there is no need to aggregate experts' judgements, and the process directly moves to step 4.

Step 4: Transfer UFNs into fuzzy sets.

UFNs are then transferred into fuzzy sets according to E.q. 4-2, 4-4, 4-5, 4-6. The fuzzy sets $\tilde{A}_{FF}$, $\tilde{A}_{CP}$ and $\tilde{A}_{CS}$ of the FF, CP and CS of the sub-hazard group "derailment (typical outcome)" are:

$$\tilde{A}_{FF} = \left\{ \left(u, \mu_{A_{FF}}(u)\right) | u \in [0,100], \mu_{A_{FF}}(u) = \begin{Bmatrix} 1 & u = 3.33E-2 \\ 0 & otherwise \end{Bmatrix} \right\}$$

$$\tilde{A}_{CP} = \left\{ \left(v, \mu_{A_{CP}}(v)\right) | v \in [0,1], \mu_{A_{CP}}(v) = \begin{Bmatrix} 1 & v = 0.99 \\ 0 & otherwise \end{Bmatrix} \right\}$$

$$\tilde{A}_{CS} = \left\{ \left(w, \mu_{A_{CS}}(w)\right) | w \in [0,5], \mu_{A_{CS}}(w) = \begin{Bmatrix} 1 & w = 0.005 \\ 0 & otherwise \end{Bmatrix} \right\}$$

Step 5: Fuzzy inference process.

There are 245 rules in the rulebase, as described in Section 7.2. They are subjectively defined based on expert experience and engineering judgment. The fire strength of each rule with input fuzzy sets can be calculated by E.q.4-8. Then, the fuzzy implication is applied to obtain the conclusion fuzzy sets of fired rules. The truncated MF of the conclusion fuzzy set of each rule can be obtained by E.q.4-9. Finally, all of the conclusion fuzzy sets are aggregated by Eq.4-10 to form a single fuzzy set which represents the fuzzy output of RL. For example, the fuzzy sets $\tilde{A}_{FF}$, $\tilde{A}_{CP}$ and $\tilde{A}_{CS}$ are the input fuzzy sets and are fired with all of the rules in the rulebase. However, there are only two rules with non-zero fire strength:

R_{28}: IF FF=*Rare* and CP= *Definite* and CS=*Negligible*, THEN RL=*Possible*.

R_{29}: IF FF=*Infrequent* and CP= *Definite* and CS=*Negligible*, THEN RL=*Possible*.

When input fuzzy sets are fired with Rule 28, the MFs of qualitative descriptors of Rule 28 are obtained according to E.q.4-2 and 4- 7:

$$\mu_{B_{Rare}}(u) = \begin{Bmatrix} (u-0.002)/0.004, & u \in [0.002, 0.006], \\ 1, & u \in [0.006, 0.015], \\ (u-0.04)/0.025, & u \in [0.015, 0.04], \\ 0, & otherwise \end{Bmatrix}$$

$$\mu_{B_{Definite}}(v) = \begin{Bmatrix} (v-0.8)/0.05, & v \in [0.8, 0.85], \\ 1, & v \in [0.85, 1], \\ 0, & otherwise \end{Bmatrix}$$

$$\mu_{B_{Negligible}}(w)=\begin{Bmatrix}1, & w\in[0,0.009],\\ (w-0.02)/0.011, & w\in[0.009,0.02],\\ 0, & otherwise.\end{Bmatrix}$$

$$\mu_{B_{Possible}}(x)=\begin{Bmatrix}x-1, & x\in[1,2],\\ 1, & x\in[2,4],\\ 5-x, & x\in[4,5],\\ 0, & otherwise\end{Bmatrix}.$$

The fire strength of Rule 28 α_{28} is calculated by E.q.4-8:

$$\alpha_{28}=\min\left[\max\left(\mu_{A_{FF}}(u)\wedge\mu_{B_{Rare}}(u)\right),\max\left(\mu_{A_{CP}}(v)\wedge\mu_{B_{Definite}}(v)\right),\max\left(\mu_{A_{CS}}(w)\wedge\mu_{B_{Negligible}}(w)\right)\right]$$
$$=\min\left(0.25,1,1\right)=0.25.$$

The MF conclusion fuzzy set of Rule 28 $\mu'_{B_{RL}^{28}}(x)$ is calculated by E.q.4-9:

$$\mu'_{B_{RL}^{28}}(x)=\alpha_{28}\wedge\mu_{B_{Possible}}(x)=\begin{Bmatrix}x-1, & x\in[1,2],\\ 0.25, & x\in[2,4],\\ 5-x, & x\in[4,5],\\ 0, & otherwise\end{Bmatrix}.$$

The MF conclusion fuzzy set of Rule 29 $\mu'_{B_{RL}^{29}}(x)$ is also calculated:

$$\mu'_{B_{RL}^{29}}(x)=\alpha_{29}\wedge\mu_{B_{Possible}}(x)=\begin{Bmatrix}x-1, & x\in[1,2],\\ 0.75, & x\in[2,4],\\ 5-x, & x\in[4,5],\\ 0, & otherwise\end{Bmatrix},\alpha_{29}=0.75.$$

The MF of final output RL is obtained by E.q.4-10:

$$\mu'_{B_{RL}}(x)=\bigvee_{i=1}^{245}\mu'_{B_{RL}^{i}}(x)=\mu'_{B_{RL}^{1}}\vee\mu'_{B_{RL}^{2}}\vee,\ldots,\vee\mu'_{B_{RL}^{28}}\vee\mu'_{B_{RL}^{29}}\vee,\ldots,\vee\mu'_{B_{RL}^{245}}$$

$$= \mu'_{B_{RL}^{28}} \vee \mu'_{B_{RL}^{29}} = \left\{ \begin{array}{ll} x-1, & x \in [1,2], \\ 0.75, & x \in [2,4], \\ 5-x, & x \in [4,5], \\ 0, & otherwise \end{array} \right\}.$$

Step 6: Defuzzification.

The crisp value of RL can be defuzzified from the fuzzy set of the output RL by E.q.4-11. The RL of the sub-hazard group "derailment (typical outcome)" is finally obtained:

$$RL = \frac{\sum_{j=1}^{10} \mu'_{B_{RL}}\left(x_j\right) \cdot x_j}{\sum_{j=1}^{10} \mu'_{B_{RL}}\left(x_j\right)} = \frac{0.75 \times 2 + 0.75 \times 3 + 0.75 \times 4}{0.75 + 0.75 + 0.75} = 3,$$

where the number of quantisation levels is set to 10, which is appropriate to defuzzify the output fuzzy set.

By following the six steps above, all of the RLs of sub-hazard groups are calculated and the result is shown in Table 7-9. As the sub-hazard groups are of equal importance to their hazard groups, there is no need to perform Fuzzy-AHP analysis to obtain the RL of hazard groups, so the RLs of hazard groups are obtained by aggregating fuzzy sets of the RLs of the sub-hazard groups and then performing a defuzzification operation based on the aggregated fuzzy sets. The results of RLs for hazard groups are listed in Table 7-10 Risk ranking from Metronet method

.

7.4 Fuzzy-AHP Risk Estimation

In order to assess the RL at railway depot level, the relative importance of hazard groups' contribution to the RL of shunting at Hammersmith depot is considered and estimated by Fuzzy-AHP using RISRAS, which is quantified as WFs in the developed risk model. Thus, the WFs of hazard groups in this phase are calculated firstly and then synthesised with the RLs of hazard groups to finally determine the RL at railway depot level. The process is demonstrated as follows:

Step 1: Establish estimation scheme.

The judgments were made on the basis of the estimation scheme, which all the experts agreed with. The estimation scheme used in the case is shown in Table 3-1.

Step 2: Pair-wise compare factors in risk tree.

Experts' judgments about relative importance between hazard groups are shown in Table 7-6. Thanks to improved Fuzzy-AHP, there are only 6 comparisons that have been made. Experts can use linguistic terms, numerical numbers, ranges and fuzzy numbers to present their opinions. For example, in comparison 1 in Table 7-6, experts agree that DHG is more important than CHG. However, they have different opinions on the degree of importance, and E1, E2, E3, E4 and E5 chose "WI", "BWS", "4, 6", "4, 5" and "BWS" respectively. The judgements can be easily collected by using the questionnaires provided by RISRAS, as described in Section 5.3.2.

Step 3: Convert inputs into UFNs.

The judgements are then converted into UFNs according to Table 4-1, and the converted UFNs are listed in Table 7-6.

Step 4: Aggregate UFNs.

The converted UFNs are then aggregated with respect to EIs in Table 7-5 by Eq. 4-3. For example, the aggregated UFN $A_{1,2}$ of comparison 1 in Table 7-6 is obtained by Eq.4- 3:

$$A_{1,2}=\left\{a_{1,2},b_{1,2},c_{1,2},d_{1,2}\right\}=\left\{\frac{\sum_{k=1}^{5}a_k EI_k}{\sum_{k=1}^{5}EI_k},\frac{\sum_{k=1}^{5}b_k EI_k}{\sum_{k=1}^{5}EI_k},\frac{\sum_{k=1}^{5}c_k EI_k}{\sum_{k=1}^{5}EI_k},\frac{\sum_{k=1}^{5}d_k EI_k}{\sum_{k=1}^{5}EI_k}\right\}$$

$$=\left\{\frac{1\times0.21+3\times0.24+...+3\times0.16}{0.21+0.24+...+0.16},...,\frac{2\times0.21+5\times0.24+...+5\times0.16}{0.21+0.24+...+0.16}\right\}=\left\{2.94,4,4,5\right\}$$

where a_k, b_k, c_k and d_k are the four parameters in a converted UFN. All the aggregated UNFs are shown in**Error! Reference source not found.**.

Step 5: Calculate fuzzy WFs from comparison matrix.

Then, following steps 1 to 4 in Section 3.4.2.2, the entire comparison matrix for the hazard group can be developed. The comparison matrix M is then established with these aggregated UNFs according to Eq. 4-12.

$$M=\left[A_{i,j}\right]=\begin{bmatrix} A_{1,1} & A_{1,2} & \cdots & A_{1,7} \\ A_{2,1} & A_{2,2} & \cdots & A_{2,7} \\ \vdots & \vdots & \ddots & \vdots \\ A_{7,1} & A_{7,2} & \cdots & A_{7,7} \end{bmatrix}, i,j=1,2,\dots,7$$

$$=\begin{bmatrix} 1,1,1,1 & A_{1,2} & \cdots & A_{1,7} \\ A_{2,1} & 1,1,1,1 & \cdots & A_{2,7} \\ \vdots & \vdots & \ddots & \vdots \\ A_{7,1} & A_{7,2} & \cdots & 1,1,1,1 \end{bmatrix}.$$

By using propositions 3 and 4 as described in Section 3.4.2.2, the entire comparison matrix can be obtained, as shown in Table 7-7. However, for example, value $A_{1,6}$ is not in the interval [1/9,9], the following transformation functions must be applied according to Eq. 3-20 .

$$f(x_a)=x_a^{1/\log_9^{897.12}}, f(x_b)=x_b^{1/\log_9^{897.12}}, f(x_c)=x_c^{1/\log_9^{897.12}}, f(x_d)=x_d^{1/\log_9^{897.12}}$$

Table 7-8 lists the transferred entries that are used as the completed comparison matrix M for the Fuzzy-AHP process.

The UFN geometric mean $\bar{A}_i$ of the ith row in the comparison matrix is calculated by Eq. 4-13:

$$\bar{A}_1 = \left\{\bar{a}_1, \bar{b}_1, \bar{c}_1, \bar{d}_1\right\} = \left\{\sqrt[7]{\prod_{j=1}^{7} a_{1,j}}, \sqrt[7]{\prod_{j=1}^{7} b_{1,j}}, \sqrt[7]{\prod_{j=1}^{7} c_{1,j}}, \sqrt[7]{\prod_{j=1}^{7} d_{1,j}}\right\}$$

$$= \left\{\sqrt[7]{1 \times 1.41 \times ... \times 1.95}, ..., \sqrt[7]{1 \times 1.68 \times ... \times 5.51}\right\} = \left\{1.894, 2.394, 2.394, 3.254\right\}$$

$$\bar{A}_2 = \{1.305, 1.529, 1.529, 1.982\}$$

$$\bar{A}_3 = \{0.940, 1.052, 1.052, 1.329\}$$

$$\bar{A}_4 = \{0.854, 1.052, 1.052, 1.170\}$$

$$\bar{A}_5 = \{0.571, 0.704, 0.704, 0.804\}$$

$$\bar{A}_6 = \{0.355, 0.449, 0.449, 0.537\}$$

$$\bar{A}_7 = \{0.590, 0.781, 0.781, 0.973\}$$

Then fuzzy WFs W_i of hazard groups are calculated with $\bar{A}_i$ by Eq.4-14.

$$W_1 = \left\{a_1, b_1, c_1, d_1\right\} = \left\{\frac{\bar{a}_1}{\sum_{i=1}^{7} \bar{d}_i}, \frac{\bar{b}_1}{\sum_{i=1}^{7} \bar{c}_i}, \frac{\bar{c}_1}{\sum_{i=1}^{7} \bar{b}_i}, \frac{\bar{d}_1}{\sum_{i=1}^{7} \bar{a}_i}\right\}$$

$$= \left\{\frac{1.305}{1.305 + 0.940 + ... + 0.590}, ..., \frac{1.982}{1.982 + 1.329 + ... + 0.973}\right\} = \left\{0.190, 0.301, 0.301, 0.500\right\}$$

$$W_2 = \left\{0.130, 0.192, 0.192, 0.305\right\}$$

$$W_3 = \left\{0.094, 0.132, 0.132, 0.204\right\}$$

$$W_4 = \left\{0.085, 0.132, 0.132, 0.180\right\}$$

$$W_5 = \left\{0.057, 0.088, 0.088, 0.124\right\}$$

$$W_6 = \left\{0.035, 0.056, 0.056, 0.082\right\}$$

$$W_7 = \left\{0.059, 0.098, 0.098, 0.150\right\}$$

Step 6: Defuzzification and normalisation.

The crisp value w_i' of fuzzy WF W_i can be calculated by Eq. 4-15.

$$w_1' = \frac{a_1 + 2(b_1 + c_1) + d_1}{6} = \frac{0.190 + 2 \times (0.301 + 0.301) + 0.5}{6} = 0.315$$

$$w_2' = 0.201$$

$$w_3' = 0.138$$

$$w_4' = 0.132$$

$$w_5' = 0.090$$

$$w_6' = 0.057$$

$$w_7' = 0.100$$

The final WF of hazardous groups WF_i is obtained by Eq. 4-16:

$$WF_1 = \frac{w_1'}{\sum_{i=1}^{7} w_1'} = \frac{0.315}{0.315 + 0.201 + ... + 0.100} = 0.31$$

$$WF_2 = 0.19$$

$$WF_3 = 0.13$$

$$WF_4 = 0.13$$

$$WF_5 = 0.09$$

$$WF_6 = 0.06$$

$$WF_7 = 0.10$$

Step7: RLs and WFs synthesis.

Once the WFs of hazard groups are obtained, the RL at railway depot level RL_{Depot} can be derived from the synthesis of the hazard groups' WFs and RLs using Eq. 4-17.

$$RL_{Depot} = \sum_{i=1}^{7} RL_i \cdot WF_i = 2.31 \times 0.31 + 3.30 \times 0.19 + ... + 3.54 \times 0.10 = 2.99$$

which indicates that the overall RL of shunting at Hammersmith depot is 2.99 belonging to "Possible" with a belief of 100 percent.

All these steps described in the risk estimation phases are coded into RISRAS. Users are generally required to complete an excel file based questionnaire for the analysis of WFs and then to input the data of FF, CP and CS into the system via an excel file based input template file and click the "Run" button to achieve the final results, which can be exported into an excel file by clicking the "Save" button. The overall procedures are demonstrated in Figure 7-3.

Comparison	**E1**		**E2**		**E3**		**E4**		**E5**		**Aggregated UFNs**
	Judgment	UFNs	Judgment	UFNs	Judgment	UFNs	Judgment	UFNs	Judgment	UFNs	
DHG vs. CHG ($A_{1,2}$)	WI	1,1,1,2	BWS	3,4,4,5	4, 6	4,5,5,6	4, 5	4,4.5,4.5,6	BWS	3,4,4,5	2.94,4.00,4.00,5.00
CHG vs. TfHG ($A_{2,3}$)	WI	2,3,3,4	BWS	3,4,4,5	BWS	3,4,4,5	SI	4,5,5,6	BWS	3,4,4,5	2.38,3.18,3.18,3.99
TfHG vs. EHG ($A_{3,4}$)	EQ	1,1,1,2	EQ	1,1,1,2	EQ	1,1,1,2	EQ	1,1,1,2	EQ	1,1,1,2	1.00,1.00,1.00,2.00
EHG vs. SHG ($A_{4,5}$)	BWS	3,4,4,5	BWS	3,4,4,5	WI	2,3,3,4	BWS	3,4,4,5	BEW	1,2,2,3	2.47,3.47,3.47,4.47
SHG vs. FHG ($A_{5,6}$)	BWS	3,4,4,5	BWS	3,4,4,5	SI	4,5,5,6	WI	2,3,3,4	BWS	3,4,4,5	3.03,4.03,4.03,5.03
TsHG vs. FHG ($A_{7,6}$)	BSV	5,6,6,7	SI	4,5,5,6	BSV	5,6,6,7	BSV	5,6,6,7	SI	4,5,5,6	4.55,5.56,5.56,6.67

Table 7-6 Expert judgements

$A_{i,j}$	1	2	3	4	5	6	7
1	1.00,1.00,1.00, 1.00	2.94,4.00,4.00, 5.00	7.00,12.72,12.72,19.95	7.00,12.72,12.72,39.90	17.28,44.14,44.14,178.35	52.37,177.88,177.88,897.12	7.85,32.00,32.00,197.19
2	0.20,0.25,0.25, 0.34	1.00,1.00,1.00, 1.00	2.38,3.18,3.18, 3.99	2.38,3.18,3.18, 7.98	5.88,11.03,11.03,35.67	17.81,44.47,44.47,179.42	2.67,8.00,8.00, 39.44
3	0.05,0.08,0.08, 0.14	0.25,0.31,0.31, 0.42	1.00,1.00,1.00, 1.00	1,1,1,2	2.47,3.47,3.47, 8.94	7.48,13.98,13.99,44.97	1.12,2.52,2.52, 9.88
4	0.03,0.08,0.08, 0.14	0.13,0.31,0.31, 0.42	0.50, 1.00,1.00, 1.00	1.00,1.00,1.00, 1.00	2.47,3.47,3.47, 4.47	7.48,13.98,13.98,22.48	1.12,2.52,2.52, 4.94
5	0.01,0.02,0.02, 0.06	0.03,0.09,0.09, 0.17	0.11,0.29,0.29, 0.40	0.22,0.29,0.29, 0.40	1.00,1.00,1.00, 1.00	3.03,4.03,4.03, 5.03	0.45,0.72,0.72, 1.11
6	1.11e-3,5.62e-3,5.62e-3,0.02	5.57e-3,0.02,0.02,0.06	0.02,0.07,0.07, 0.13	0.04,0.07,0.07, 0.13	0.20,0.25,0.25, 0.33	1.00,1.00,1.00, 1.00	0.15,0.18,0.18, 0.22
7	5.07e-3,0.03,0.03,0.13	0.03,0.12,0.12, 0.37	0.10,0.40,0.40, 0.89	0.20,0.40,0.40, 0.89	0.90,1.38,1.38, 2.20	4.55,5.56,5.56, 6.67	1.00,1.00,1.00, 1.00

Table 7-7 Pairwise comparison matrix M established for Hammersmith depot

$A_{i,j}$	1	2	3	4	5	6	7
1	1.00,1.00,1.00, 1.00	1.42,1.57,1.57, 1.68	1.88,2.27,2.27, 2.63	1.88,2.27,2.27, 3.29	2.51,3.40,3.40, 5.34	3.59,5.34,5.34, 9.00	1.95,3.06,3.06, 5.52
2	0.59,0.64,0.64, 0.71	1.00,1.00,1.00, 1.00	1.32,1.45,1.45, 1.56	1.32,1.45,1.45, 1.96	1.77,2.17,2.17, 3.17	2.54,3.41,3.41, 5.35	1.37,1.96,1.96, 3.28
3	0.38,0.44,0.44, 0.53	0.64,0.69,0.69, 0.76	1.00,1.00,1.00, 1.00	1.00,1.00,1.00, 1.25	1.34,1.49,1.49, 2.03	1.92,2.35,2.35, 3.42	1.04,1.35,1.35, 2.10
4	0.30,0.44,0.44, 0.53	0.51,0.69,0.69, 0.76	0.80,1.00,1.00, 1.00,	1.00,1.00,1.00, 1.00	1.34,1.49,1.49, 1.62	1.92,2.35,2.35, 2.73	1.04,1.35,1.35, 1.68
5	0.19,0.29,0.29, 0.40	0.32,0.46,0.46, 0.56	0.49,0.67,0.67, 0.75	0.62,0.67,0.67, 0.75	1.00,1.00,1.00, 1.00	1.43,1.57,1.57, 1.69	0.77,0.90,0.90, 1.03
6	0.11,0.19,0.19, 0.28	0.19,0.29,0.29, 0.39	0.29,0.43,0.43, 0.52	0.37,0.43,0.43, 0.52	0.59,0.64,0.64, 0.70	1.00,1.00,1.00, 1.00	0.54,0.57,0.57, 0.61
7	0.18,0.33,0.33, 0.51	0.30,0.51,0.51, 0.73	0.48,0.74,0.74, 0.96	0.60,0.74,0.74, 0.96	0.97,1.11,1.11, 1.29	1.63,1.74,1.74, 1.85	1.00,1.00,1.00, 1.00

Table 7-8 Final Pairwise comparison matrix M established for Hammersmith depot

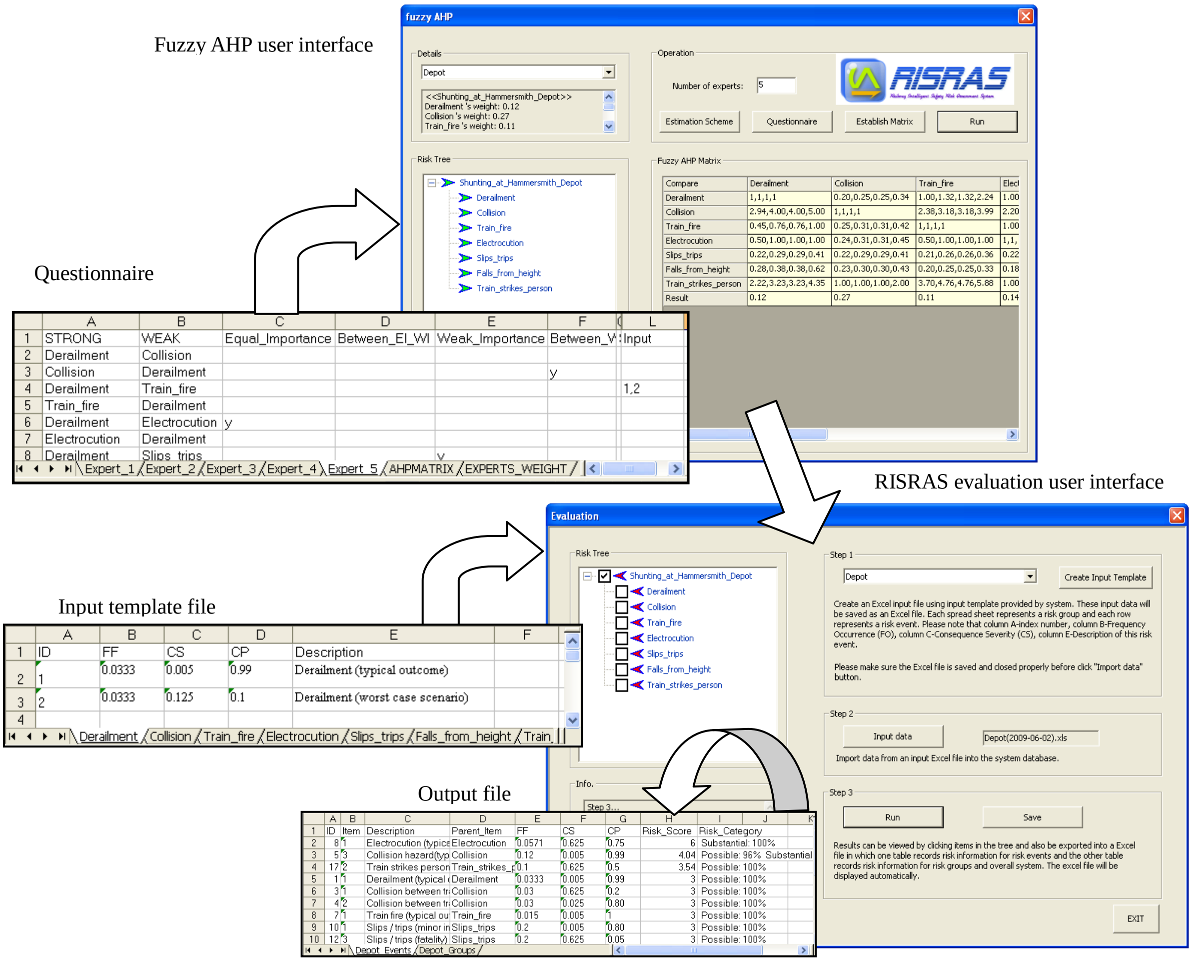


Figure 7-3 Using RISRAS in the assessment

7.5 Risk Response Phase

The overall RL of shunting at Hammersmith depot is 2.99, belonging to the risk category “Possible” with a belief of 100%. This requires risk reduction measures to reduce the overall RL of depot to ALARP. Seven hazard groups effect the overall RL estimation at the Hammersmith depot. It should be noted that each hazard group contributes a different weight value to the overall RL of the depot. It can be seen from Table 7-12 that the major contributions are from the hazard groups “Derailment”, “Collision” and “Electrocution”, which contributed 24%, 21% and 19% respectively to the overall RL of shunting at Hammersmith depot. Each hazard group consists of a number of hazardous events. For example, in this case, there are six main hazardous events in the “Derailment” hazard group, which are track related faults, signal related faults, rolling stock faults, structural failures, falling objects from trains, and human errors, which result in derailment. Based on the accident and incident reports and statistics, the majority of derailment risk (92%) is put down to human errors such as overspending and incorrect routing. Therefore, in order to reduce the RLs of derailment, staff training should be provided to shunters, signallers and drivers; at the same time speed should be limited at the depot, liaison between Metronet Rail shunters and signallers should be improved, and reference manual procedures should be provided. The other potential control measures to reduce derailment risks include track maintenance and inspection training of track staff to reduce track related faults; signal/points maintenance and inspection of engineering controls, e.g. interlocking, training and competence of signal maintenance staff to reduce signalling related faults; fleet maintenance and inspection training and competence of fleet staff and brake testing before moving to reduce rolling stock related faults; civil maintenance and inspection training and competence of civil staff to reduce structural failures; fleet maintenance and inspection training and competence of fleet staff to reduce the objects from trains risk.

The hazard groups “Train fire”, “Train strikes person”, “Slips/trips” and “Falls from height” contribute less than the above hazard groups with 13%, 11%, 7% and 4%, respectively. Although these hazard groups have relatively a minor contribution to the overall RL of shunting at Hammersmith depot, the control measures are still carried out to reduce those hazardous events whose RLs fall in the transition region, i.e. “Possible” and “Substantial”. For example, the hazard group of “Train fire” contributes 10% to the overall RL of depot. As the major fire related hazardous events lead to system failure or personal injury and health hazards include arcing and mechanical failure, the suggested control measures are to provide maintenance and inspection of fleet and track assets regularly. In addition, fire extinguishers installed in the cab could mitigate the consequences and reduce the chance of severe outcomes.

the results using the method proposed herein were compared with earlier method developed by Huang (reference) and Metronet, as shown in Table 7-10, the risk ranking from the proposed model is slightly different. For example, within the “Slips/trips” sub-hazard group, “Slips/trips (major)” and “Slip/trip (fatality)” rank higher than “Slips/trip (minor injury)” in the results from Metronet Rail assessment, whereas in Huang’s assessment those sub-hazard groups are classified in the same risk category, but from the proposed risk model, “Slips/trip (minor injury)” and “Slip/trip (fatality)” rank higher than “Slips/trips (major)”. After further investigation of the data, the results from the proposed model are more conversable, as the consequence of “Slips/trip (minor injury)” is low but with a higher probability of occurrence, and such an event should be highlighted in the assessment. The results from the proposed model indicate that “Collision (typical outcome)” is of high risk due to its higher consequence probability, which should not be ignored. However, the results from these two methods both agree that “Electrocution (typical outcome)” and “Train strikes person (fatality)” are of higher risk than others.

Furthermore, the outcomes of the assessment from the proposed model are represented by risk degrees and the defined risk categories of RLs with a belief of percentage. The Metronet method cannot provide a belief percentage in the corresponding risk category for each sub-hazard group. Compared with the method applied by Metronet, the proposed model can provide an extra risk ranking at hazard group level. The overall system risk level can also be obtained. With the application of Fuzzy-AHP, even the societal risk created by the operation can be taken into account. According to the results, different contributions of hazard groups to the failure of the system operation could be easily identified. In Huang’s method, as FRA and Fuzzy-AHP have been applied in the assessment, it can also provide risk information in the format of risk score, risk category and risk contribution. However, it cannot provide satisfactory risk ranking as CP is not considered in the assessment, which can be obtained from expert judgements. In summary, the proposed model can provide much more useful risk information than the Metronet method and Dr Huang’s method. It facilitates decision makers to identify hazard groups in a high risk level and reduce risk more effectively and efficiently.

Table 7-9 Shunting at Hammersmith depot

			Proposed model					
Operation	**Hazard Groups**	**Index**	**Sub-hazard Groups**	**Failure Frequency**	**Consequence Probability**	**Consequence Severity**	**Risk Score**	**Risk Category**
Shunting at Hammersmith depot	Derailment	1	Derailment (typical outcome)	3.33E-02	99%	0.005	3.00	Possible: 100%
		2	Derailment (worst case scenario)	3.33E-02	1%	0.125	0.81	Low: 100%
	Collision	3	Collision between trains (worst case scenario)	3.00E-02	20%	0.625	2.52	Possible: 100%
		4	Collision between trains (typical outcome)	3.00E-02	80%	0.025	3.00	Possible: 100%
		5	Collision hazard (typical outcome)	1.20E-01	99%	0.005	4.04	Possible: 96% Substantial: 4%
		6	Collision hazard (worst case scenario)	1.20E-01	1%	0.125	0.82	Low: 100%
	Train fire	7	Train fire (typical outcome)	1.50E-02	100%	0.005	3.00	Possible: 100%
	Electrocution	8	Electrocution (typical outcome)	5.71E-02	75%	0.625	6.00	Substantial: 100%
		9	Electrocution (best case scenario)	5.71E-02	25%	0.125	0.80	Low: 100%
	Slips/trips	10	Slips / trips (minor injury)	2.00E-01	80%	0.005	3.00	Possible: 100%
		11	Slips / trips (major injury)	2.00E-01	15%	0.125	0.80	Low: 100%
		12	Slips / trips (fatality)	2.00E-01	5%	0.625	3.00	Possible: 100%
	Falls from height	13	Falls from height (minor injury)	1.43E-02	15%	0.005	0.75	Low: 100%
		14	Falls from height (major injury)	1.43E-02	80%	0.125	3.00	Possible: 100%
		15	Falls from height (fatality)	1.43E-02	5%	0.625	0.75	Low: 100%
	Train strikes person	16	Train strikes person (major injury)	1.00E-01	50%	0.125	3.00	Possible: 100%
		17	Train strikes person (fatality)	1.00E-01	50%	0.625	3.54	Possible: 100%

	Metronet method		**Huang's method**		**Proposed methodl**	
Sub-hazard groups	**Risk rankings**	**Indicate risk ranking**	**Risk Score**	**Risk Category**	**Risk Score**	**Risk Category**
Electrocution (typical outcome)	7	Medium	7.42	Substantial: 100%	6.00	Substantial: 100%
Train strikes person (fatality)	7	Medium	8.00	Substantial: 100%	3.54	Possible: 100%
Collision between trains (worst case scenario)	6	Low	5.00	Possible: 100%	2.52	Possible: 100%
Slips / trips (major injury)	6	Low	5.00	Possible: 100%	0.80	Low: 100%
Slips / trips (fatality)	6	Low	5.00	Possible: 100%	3.00	Possible: 100%
Train strikes person (major injury)	6	Low	5.00	Possible: 100%	3.00	Possible: 100%
Train fire (typical outcome)	5	Low	5.00	Possible: 100%	3.00	Possible: 100%
Electrocution (best case scenario)	5	Low	5.00	Possible: 100%	0.80	Low: 100%
Slips / trips (minor injury)	5	Low	5.00	Possible: 100%	3.00	Possible: 100%
Falls from height (major injury)	5	Low	5.00	Possible: 100%	3.00	Possible: 100%
Falls from height (fatality)	4	Low	5.00	Possible: 100%	0.75	Low: 100%
Derailment (worst case scenario)	4	Low	5.00	Possible: 100%	0.81	Low: 100%
Collision between trains (typical outcome)	4	Low	5.00	Possible: 100%	3.00	Possible: 100%
Collision hazard (worst case scenario)	4	Low	5.00	Possible: 100%	0.82	Low: 100%
Derailment (typical outcome)	4	Low	4.48	Possible: 100%	3.00	Possible: 100%
Collision hazard (typical outcome)	3	Low	3.34	Low: 66% Possible: 34%	4.04	Possible: 96% Substantial: 4%
Falls from height (minor injury)	2	Low	2.76	Low: 100%	0.75	Low: 100%

Table 7-10 Risk ranking from Metronet method

Operation	Index	Hazard groups	Risk Score	Risk Category
Shunting at Hammersmith depot (3.29, Possible: 100%	1	Derailment	2.31	Possible: 100%
	2	Collision	3.3	Possible: 100%
	3	Train fire	3	Possible: 100%
	4	Electrocution	4.47	Possible: 53% Substantial: 47%
	5	Slips/trips	2.4	Possible: 100%
	6	Falls from height	2.17	Possible: 100%
	7	Train strikes person	3.54	Possible: 100%

Table 7-11 RLs of hazard group in Hammersmith depot

Operation	Index	Hazard groups	WF	Contribution
Shunting at Hammersmith Depot	1	Derailment	0.31	24%
	2	Collision	0.19	21%
	4	Electrocution	0.13	19%
	3	Train fire	0.13	13%
	7	Train strikes person	0.10	11%
	5	Slips/trips	0.09	7%
	6	Falls from height	0.06	4%

Table 7-12 Hazard groups' risk contribution ranking for Hammersmith depot

7.6 Summary

Traditionally, risk assessment techniques currently used in the railway industry have adopted a probabilistic approach, which heavily rely on the availability and accuracy of data; sometimes they are unable to deal adequately with incomplete or uncertain data. This chapter presents a case study on risk assessment of shunting at Hammersmith depot using the proposed risk assessment model based on FRA and improved Fuzzy-AHP. The outcomes of risk assessment are the RLs of hazardous events, hazard groups and a railway system and corresponding risk categories as well as risk contributions. It will provide railway risk analysts, managers and engineers with useful information to improve safety management and set safety standards. Some screen shots of the proposed railway risk assessment system are shown in Figure 7-3. This system consists of a user-friendly interface that controls the risk assessment process including a project manager, an excel processor and a database management system, which is easy to use and update. Compared with the conventional methods, the advantages of the proposed risk assessment system can be summarised as:

(1) it can handle expert knowledge, engineering judgments and historical risk data for the railway risk assessment in a consistent manner;

(2) it can use imprecise, ambiguous and uncertainty information in the assessment;

(3) the risk can be evaluated directly using linguistic expressions which are employed in the risk assessment;

(4) the risk can be assessed effectively on the basis of the knowledge base built by transforming information from various sources;

(5) it provides a more flexible structure for combining failure frequency, consequences and consequence probability in risk analysis.

CHAPTER 8: APPLICATION OF RISK BASED MAINTENANCE DECISION MAKING MODEL TO A RAILWAY TRACK SYSTEM

8.1 Introduction

This chapter presents an illustrative example of a track system risk assessment that is used to demonstrate the application of the proposed risk-based decision making method. The risk assessment will be performed to assess current risks at component level, subsystem level and system level. The RLs of the track system are calculated based on the risk model. Next, the cost model is used to calculate the relevant cost of each proposed maintenance option. Then, each maintenance option is assessed by using TOPHSIS method to obtain its preference degree. Finally, the maintenance decision can be made based on the preference degrees of maintenance options.

8.2 Risk Assessment of a Track System

A track system can be divided into three levels, i.e. system level, subsystem level and component level, as shown in Figure 8-1. At subsystem level, two subsystems, namely, "*Track component*" subsystem and "*Subgrade*" subsystem, can be identified. "*Track component*" subsystem, which supports and distributes train loads, includes six main components. They are "*Rail*", "*Fishplate*", "*Fastening*", "*Pad*", "*Ballast*" and "*Sleeper*". "*Subgrade*" subsystem, on which the train loads, after adequate distribution in the "*track component*" subsystem, are transferred. It covers two components, i.e. "*Formation layer*" and "*Base*". Each component consists of a number of failure modes that are described below.

- "*Rail*" covers four failure modes. i.e. "*Rail defect*", "*Rail fatigue*", "*Poor support*" and "*Damaged by powered wheel*". All failures are potentially catastrophic and may possibly result in a derailment.
- "*Fishplate*" includes failure mode "*Inadequate rail joint support*" which is the main cause of cracked fishplates. The failure of "*Fishplate*" may lead to the wheelsets falling in between the rails and rail deformation.
- "*Fastening*" consists of two failure modes, "*Clip wear*" and "*Screw loos*e". The failure of individual fastenings does not present any significant threat to the safety of trains, but there is a possibility that the failed fastening could transfer additional loading onto adjacent fastenings which could result in a rapid escalation of failures.
- "*Pad*" includes "*Pad degradation*" causing a pad split or thinned and failing to assist in keeping the rail fastenings tight.
- "*Ballast*" has one failure mode, "*Load related failure*". Due to repeated dynamic loading, the size and shape of the ballast is damaged gradually, and then ballast is no longer able to support the track both laterally and vertically.
- "*Sleeper*" consists of two failure modes, "*Load damage*" and "*Maintenance damage*". The failed sleepers may be incapable of supporting the track and/or retaining the rails to gauge.
- "*Formation layer*" and "*Base*" are two components of the "*Subgrade*" subsystem. Both of them have three failure modes, i.e. "*Load related failure*", "*Soil related failure*" and "*Environment related failure*". The failure of the above two components may lead to poor performance in supporting the railway track under traffic loads.

According to bottom up assessment approach as stated in Section 2.3.3.2, risk assessment is carried out from component level to assess failure modes. On the basis of the proposed safety risk model, the input parameters are failure frequency (FF), consequence probability (CP) and consequence severity (CS) of failure modes. FRA is applied to assess the risk levels (RLs) of failure modes. Based on the RLs of failure modes, the RL of the corresponding component can be obtained by the fuzzy aggregation operation of FRA. The RL of the subsystem is derived by synthesizing the RLs of components and corresponding weights which are produced by fuzzy-AHP., Finally, the track system RL can be obtained. The outputs of the track system risk assessment are RLs of failure modes, components, subsystems and the overall RL of the track system with risk scores located from 0 to 10 and risk categories as "*Low*", "*Possibl*e", "*Substantial*" and "*High*" with a percentage belief.

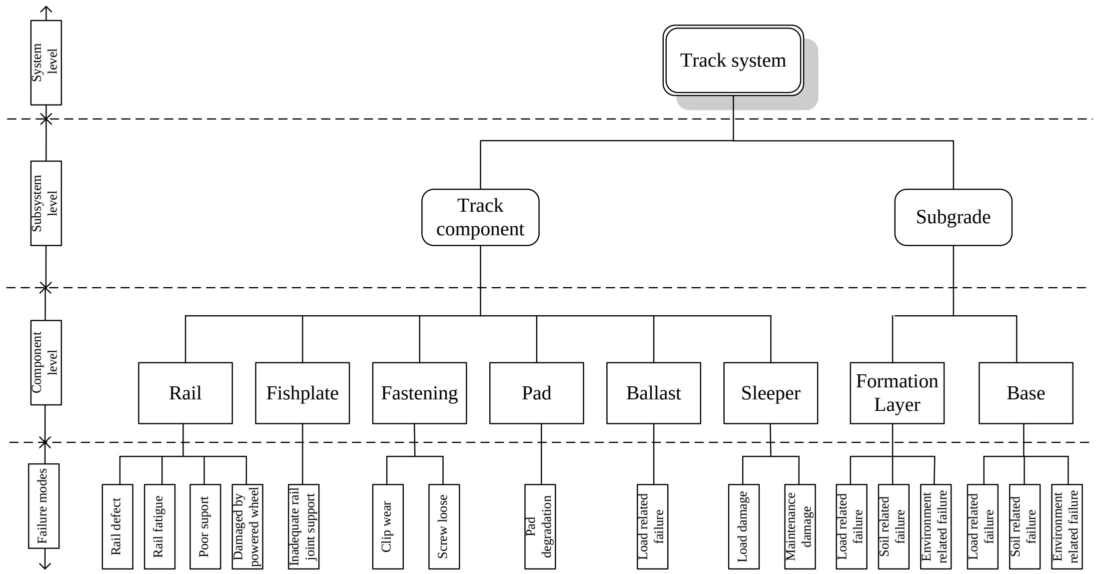


Figure 8-1 The risk tree for track system risk analysis

8.2.1 Risk assessment at component level

The risk parameters of FF, CP and CS, the output RL and their related rulebase for this risk analysis are defined as described as follows. Those parameters are all characterised by numbers of trapezoidal MFs. Six qualitative descriptors, such as "*Very low*", "*Low*", "*Reasonably low*", "*Average*", "*Frequent*" and "*Highly frequent*" are used to describe FF, as shown in Table 8-1. For example, qualitative descriptor "*low*" is characterised by a trapezoidal MF whose vertex values are 0.5, 1, 2, and 4. Five qualitative descriptors "*Negligible*", "*Marginal*", "*Moderate*", "*Critical*" and "*Catastrophic*" are used to describe CS, in which, for example, the qualitative descriptor "Catastrophic" is characterised by a trapezoidal MF whose vertex values are 6, 7, 8, and 9, as shown in

Table 8-2. Seven qualitative descriptors, such as “Highly unlikely”, “Unlikely”, “Reasonably unlikely”, “Likely”, “Reasonably likely”, “Highly likely” and “Definite” are used to describe CP, in which, for example, the qualitative descriptor “Definite” is characterised by a trapezoidal MF whose vertex values are 0.8, 0.85, 1, and 1 as shown in Table 8-3. The output RL is characterised as “*Low*”, “*Possible*”, “*Substantial*” and “*High*” as shown in Table 8-4. For example, qualitative descriptor “*Low*” is defined by a trapezoidal MF that four parameters of the MF are 0, 0, 2, and 3.

An FRA rulebase is developed and determined by experienced experts, as shown in Figure 8-2 . In this case, there are 210 rules defined in the rulebase. For example, the rule at the top left of the matrix of CS = Negligible would be expressed as follows:

IF FF is Remote and CP is Highly unlikely and CS = Negligible, THEN RL is Low

Index	Qualitative descriptors	Description	Numerical value (events/ 10 million tons)	Parametres of MFs (trapezoid)
1	Very low	Failure is unlikely	<1.0	0.00,0.00,0.50,1.00
2	Low	Relatively few failures	1.1-3.0	0.50,1.00,2.00,4.00
3	Reasonably low	Between low and average	3.1-8.0	2.00,4.00,5.00,9.00
4	Average	Occasional failures	8.1-15.0	5.00,9.00,11.00,16.00
5	Frequent	Repeated failures	15.1-25.0	11.00,16.00,19.00,25.00
6	Highly frequent	Failure is almost inevitable	>25.1	19.00,25.00,32.00,32.00

Table 8-1 Definitions of qualitative descriptors of FF for track system

Index	Qualitative descriptors	Description	Numerical ranking	Parametres of MFs (trapezoid)
1	Negligible	Involving no injury and negligible damage to the system	0,1	0.00,0.00,1.00,2.00
2	Marginal	Involving minor system damage and/or minor injury	2,3	1.00,2.00,3.00,4.00
3	Moderate	Involving failure causes some operational dissatisfaction	4,5,6	3.00,4.00,5.00,7.00
4	Critical	Involving major system damages and/or sever injury	7,8	5.00,7.00,8.00,9.00
5	Catastrophic	Involving system loss and/or death.	9,10	8.00,9.00,10.00,10.00

Table 8-2 Definitions of qualitative descriptors of CS for track system

Rank	**Qualitative descriptors**	**Description**	**Parameters of MFs (trapezoid)**
1	Highly unlikely	The occurrence likelihood of accident is highly unlikely.	0.00, 0.00, 0.15, 0.20
2	Unlikely	The occurrence likelihood of accident is unlikely but possible given the occurrence of the failure event.	0.15, 0.20, 0.25, 0.30
3	Reasonably unlikely	The occurrence likelihood of accident is between likely and unlikely.	0.25, 0.30, 0.35, 0.425
4	Likely	The occurrence likelihood of accident is likely.	0.35, 0.425, 0.575,0. 65
5	Reasonably likely	The occurrence likelihood of accident is between likely and highly likely.	0.575, 0.65, 0.70, 0.75
6	Highly likely	The occurrence likelihood of accident is very likely	0.70, 0.75, 0.80, 0.85
7	Definite	The accident occurs given the occurrence of the failure event.	0.80, 0.85, 1.00, 1.00

Table 8-3 Definitions of qualitative descriptors of CP for track system

Rank	Qualitative descriptors	Description	Parameters of MFs (trapezoid)
1	Low	Risk is acceptable	0, 0, 1, 2
2	Possible	Risk is tolerable but should be further reduced if it is cost-effective to do so	1, 2, 4, 5
3	Substantial	Risk must be reduced if it is reasonably practicable to do so	4, 5, 7, 8
4	High	Risk must be reduced to safe in exceptional circumstances	7, 8, 10, 10

Table 8-4 Definitions of qualitative descriptors of RL for track system

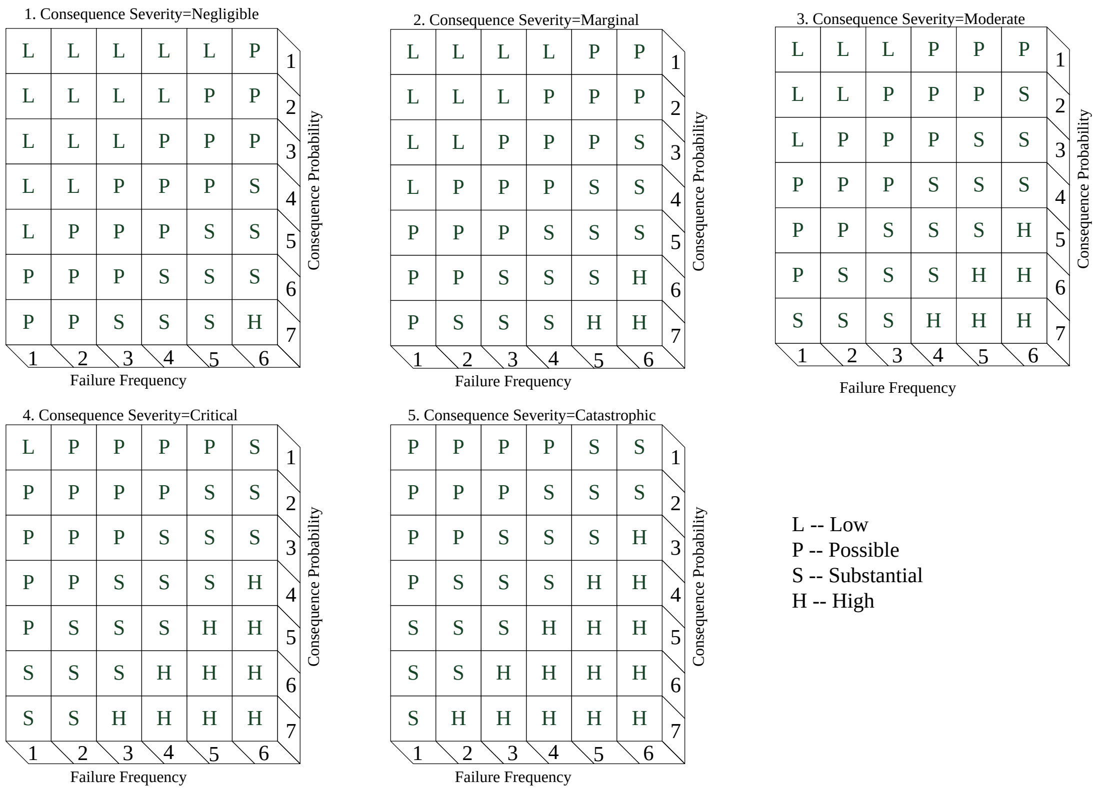


Figure 8-2 Fuzzy rule base matrices

The assessment is carried out from component level, then up to subsystem level and finally to system level. The risk data of failure modes of each component are then processed following the procedures described in Section 4. 2.3.

Step 1: Input FFs, CSs, and CPs.

As the data obtained are in numerical format, these crisp values of FF, CP and CS of failure modes are directly input into the RISRAS through the input template file. For example, the FF, CP and CS of failure mode “Defect” of “Rail” component are ‘2.0’, ‘Reasonably likely’, and ‘8.0’ respectively.

Step 2: Convert inputs into UFNs.

These crisp values are converted into corresponding UFNs according to Table 4-1. The converted UFNs A_{FF}, A_{CP}, and A_{CS} of the FF, CP and CS of failure mode “Defect” of “Rail” component are:

$$A_{FF} = \{2.0, 2.0, 2.0, 2.0\}$$
$$A_{CP} = \{0.575, 0.65, 0.70, 0.75\}$$
$$A_{CS} = \{8.0, 8.0, 8.0, 8.0\}$$

Step 3: Aggregate UFNs.

As the data are obtained from one expert judgement, there is no need to aggregate experts’ judgements and the process moves directly to step 4.

Step 4: Transfer UFNs into fuzzy sets.

UFNs are then transferred into fuzzy sets according to Eq. 4-2, 4-4, 4-5 and 4-6. The fuzzy sets $\tilde{A}_{FF}$, $\tilde{A}_{CP}$, and $\tilde{A}_{CS}$ of the FF, CP and CS of failure mode “Defect” of “Rail” component are:

$$\tilde{A}_{FF} = \left\{ \left(u, \mu_{A_{FF}}(u)\right) \mid u \in [0,100], \mu_{A_{FF}}(u) = \begin{cases} 1 & u = 2.0 \\ 0 & otherwise \end{cases} \right\}$$

$$\tilde{A}_{CP} = \left\{ \left(v, \mu_{A_{CP}}(v)\right) \mid v \in [0,1], \mu_{A_{CP}}(v) = \begin{cases} 1 \quad v \in [0.65, 0.7] \\ 0 \quad otherwise \\ (v - 0.575)/(0.65 - 0.575), v \in [0.575, 0.65] \\ (v - 0.75)/(0.7 - 0.75), v \in [0.7, 0.75] \end{cases} \right\}$$

$$\tilde{A}_{CS} = \left\{ \left(w, \mu_{A_{CS}}(w)\right) \mid w \in [0,5], \mu_{A_{CS}}(w) = \begin{cases} 1 & w = 8.0 \\ 0 & otherwise \end{cases} \right\}$$

Step 5: Fuzzy inference process.

There are 210 rules in the rulebase as described earlier in this chapter. They are subjectively defined based on expert experience and engineering judgment. The fire strength of each rule with input fuzzy sets can be calculated by Eq.4-8. Then, the fuzzy implication is applied to obtain the conclusion fuzzy sets of fired rules. The truncated MF of the conclusion fuzzy set of each rule can be obtained by Eq.4-9. Finally, all of the conclusion fuzzy sets are aggregated by Eq.4-10 to form a single fuzzy set which represents the fuzzy output of RL of failure mode. For example, the fuzzy sets $\tilde{A}_{FF}$, $\tilde{A}_{CP}$ and $\tilde{A}_{CS}$ are the input fuzzy sets and are fired with all of the rules in the rulebase. However, there are only three rules with non-zero fire strength:

R_{48}: IF FF=*Low* and CP= *Reasonably likely* and CS=*Critical*, THEN RL=*Substantial*.
R_{49}: IF FF= *Low* and CP= *Highly likely* and CS= *Critical*, THEN RL=*Substantial*.
R_{50}: IF FF= *Low* and CP=*Likely* and CS= *Critical*, THEN RL=*Possible*.

When input fuzzy sets are fired with Rule 48, the MFs of qualitative descriptors of Rule 48 are obtained according to Eqs.4-2 and 4- 7:

$$\mu_{B_{Low}}(u)=\begin{Bmatrix} (u-0.5)/(1-0.5), u\in[0.5,1], \\ 1, \quad u\in[1,2], \\ (u-4)/(2-4), \quad u\in[2,4], \\ 0, \quad otherwise \end{Bmatrix}$$

$$\mu_{B_{\text{Reasonabliy likely}}}(v)=\begin{Bmatrix} (v-0.575)/(0.65-0.575), v\in[0.575,0.65], \\ 1, \quad v\in[0.65,0.7], \\ (v-0.75)/(0.7-0.75), v\in[0.7,0.75] \\ 0, \quad otherwise \end{Bmatrix}$$

$$\mu_{B_{Critical}}(w)=\begin{Bmatrix} 1, \quad w\in[7,8], \\ (w-5)/(7-5), w\in[5,7], \\ (w-9)/(8-9), w\in[8,9], \\ 0, \quad otherwise. \end{Bmatrix}$$

$$\mu_{B_{\text{Substantial}}}(x)=\begin{Bmatrix} x-4, \quad x\in[4,5], \\ 1, \quad x\in[5,7], \\ 8-x, \quad x\in[7,8], \\ 0, \quad otherwise \end{Bmatrix}.$$

The fire strength of Rule 48 α_{48} is calculated by Eq.4-8:

$$\alpha_{48} = \min\left[\max\left(\mu_{A_{FF}}(u) \wedge \mu_{B_{Low}}(u)\right), \max\left(\mu_{A_{CP}}(v) \wedge \mu_{B_{\text{Resaonably likely}}}(v)\right), \max\left(\mu_{A_{CS}}(w) \wedge \mu_{B_{Critical}}(w)\right)\right]$$

$$= \min(1,1,1) = 1 .$$

The MF conclusion fuzzy set of Rule 48 $\mu'_{B_{RL}^{28}}(x)$ is calculated by Eq.4-9:

$$\mu'_{B_{RL}^{48}}(x) = \alpha_{48} \wedge \mu_{B_{\text{Substantial}}}(x) = \begin{Bmatrix} x-4, & x \in [4,5], \\ 1, & x \in [5,7], \\ 8-x, & x \in [7,8], \\ 0, & otherwise \end{Bmatrix} .$$

The MF conclusion fuzzy set of Rule 49 $\mu'_{B_{RL}^{49}}(x)$ can be also calculated by Eq.4-9:

$$\mu'_{B_{RL}^{49}}(x) = \alpha_{49} \wedge \mu_{B_{\text{Substantial}}}(x) = \begin{Bmatrix} x-4, & x \in [4,5], \\ 0.5, & x \in [5,7], \\ 8-x, & x \in [7,8], \\ 0, & otherwise \end{Bmatrix}, \alpha_{49} = 0.5 .$$

The MF conclusion fuzzy set of Rule 50 $\mu'_{B_{RL}^{49}}(x)$ is calculated by Eq.4-9:

$$\mu'_{B_{RL}^{50}}(x) = \alpha_{50} \wedge \mu_{B_{Possible}}(x) = \begin{Bmatrix} x-1, & x \in [1,2], \\ 0.5, & x \in [2,4], \\ 5-x, & x \in [4,5], \\ 0, & otherwise \end{Bmatrix}, \alpha_{50} = 0.5 .$$

The MF of final output RL is obtained by Eq.4-10:

$$\mu'_{B_{RL}}(x) = \mathop{\mathrm{V}}_{i=1}^{210} \mu'_{B_{RL}^{i}}(x) = \mu'_{B_{RL}^{1}} \vee \mu'_{B_{RL}^{2}} \vee, \ldots, \vee \mu'_{B_{RL}^{48}} \vee \mu'_{B_{RL}^{49}} \vee, \ldots, \vee \mu'_{B_{RL}^{210}}$$

$$= \mu'_{B_{RL}^{48}} \vee \mu'_{B_{RL}^{49}} \vee \mu'_{B_{RL}^{50}} = \left\{ \begin{array}{ll} x-1, & x \in [1,2], \\ 0.5, & x \in [2,4.5], \\ (x-4.5)/5.5, & x \in [4.5,5] \\ 1, & x \in [5,7], \\ 8-x, & x \in [7,8], \\ 0, & otherwise \end{array} \right\}.$$

Step 6: Defuzzification.

The crisp value of RL can be defuzzified from the fuzzy set of the output RL by Eq. 4-11. The RL of failure mode “Defect” of “Rail” component is finally obtained:

$$RL = \frac{\sum_{j=1}^{10} \mu'_{B_{RL}}\left(x_j\right) \cdot x_j}{\sum_{j=1}^{10} \mu'_{B_{RL}}\left(x_j\right)} = \frac{0.5\times 2 + 0.5\times 3 + 0.5\times 4 + 1\times 5 + 1\times 6 + 1\times 7}{0.5+0.5+0.5+1+1+1} = 5$$

where the number of quantization levels is set to 10 which is appropriate to defuzzify the output fuzzy set as RL ranges from 0 to 10.

Similarly, all of the RLs of failure modes can be calculated and the result is shown in Table 8-5. As the failure modes are of equal importance to their components, the RLs of components are obtained by aggregating fuzzy sets of the RLs of the failure modes and then performing a defuzzification operation based on the aggregated fuzzy sets. The results of the RLs of components are listed in Table 8-11.

Index	Components	Failure mode	FF	CP	CS	Risk Score	Risk Categories
1	Rail	Defect	2.0	Reasonably likely	8.0	5	Possible: 100%
		Fatigue	2.5	Unlikely	8.5	5.5	Possible: 50% Substantial: 50%
		Poor support	2.0	Highly unlikely	Moderate	3.58	Possible: 100%
		Damaged by powered wheel	0.9	Highly unlikely	5-8	3.8	Possible: 100%
2	Fishplate	Inadequately maintained rail joint support	2.8	Unlikely	4.7	4	Possible: 100%
						4	Possible: 100%
3	Fastening	Clip wear	4.7	Likely	1.8	4	Possible: 100%
		Screw loose	8.3	Likely	2.2	4	Possible: 100%
						3.67	Possible: 100%
4	Pad	Pad degradation	10.7	Reasonably unlikely	2.2	5.08	Possible: 92% Substantial: 8%
						3.1	Possible: 100%
5	Ballast	Performance deterioration	2	Unlikely	3.7	3.26	Possible: 100%
						2.77	Low: 23% Possible: 77%
6	Sleeper	Load damage	3.5	Likely	5.7	1.75	Low: 100%
		Maintenance damage	0.6	Unlikely	Moderate	3.75	Possible: 100%
7	Formation layer	Load related failure	0.07	Unlikely	Moderate	2.77	Low: 23% Possible: 77%
		Soil related failure	0.27	Unlikely	5.5	1.75	Low: 100%
		Environment related failure	0.04	Unlikely	4-5	4.65	Possible: 100%
8	Base	Load related failure	0.05	Unlikely	6-9	5.5	Possible: 50% Substantial: 50%
		Soil related failure	0.01	Unlikely	5.5	3.58	Possible: 100%
		Environment related failure	0.02	Highly unlikely	4.5	3.8	Possible: 100%

Table 8-5 RLs of failure modes

8.2.2 Risk assessment at overall system level

In this case study, fuzzy-AHP analysis is employed and performed at component level and subsystem level to obtain the WFs of each component and subsystem. Expert judgment will be employed to construct pairwise comparisons at component level and subsystem level, according to the estimation scheme, as shown in Table 3-1. The process of calculating the WFs of components belonging to “Track components” subsystem is demonstrated as follows:

Step 1: Establishing estimation scheme.

The judgments were made on the basis of the estimation scheme, which all of the experts agreed. The estimation scheme used in the case is shown in Table 3-1.

Step 2: Construct Pair-wise comparison factors in risk tree.

Expert judgments about the relative importance between components within the “Track components” subsystem are shown in Table 8-6. There are 5 comparisons that have been made by each expert. Similarly, experts can use linguistic terms, numerical numbers, ranges and fuzzy numbers to present their opinions. For example, in comparison 1 in Table 8-6, experts agree that “Rail” is more important than “Fishplate”, but they have different opinions on the importance degree. E1, E2, E3, E4 and E5 chose “VI”, “7,8,9”, “6,7,8”, “VI” and “6-8” respectively. These judgements are collected by using the questionnaires provided by RISRAS, as described in Section 5.3.2.

Step 3: Converting inputs into UFNs.

The judgements are then converted into UFNs according to Table 4-1, and the converted UFNs are listed in Table 8-6.

Step 4: Aggregate UFNs.

The converted UFNs are then aggregated with respect to EIs in Table 8-6 by Eq. 4-3. For example, the aggregated UFN $A_{1,2}$ of comparison 1 in Table 8-6 is obtained by Eq.4- 3:

$$A_{1,2} = \{a_{1,2}, b_{1,2}, c_{1,2}, d_{1,2}\} = \left\{ \frac{\sum_{k=1}^{5} a_k EI_k}{\sum_{k=1}^{5} EI_k}, \frac{\sum_{k=1}^{5} b_k EI_k}{\sum_{k=1}^{5} EI_k}, \frac{\sum_{k=1}^{5} c_k EI_k}{\sum_{k=1}^{5} EI_k}, \frac{\sum_{k=1}^{5} d_k EI_k}{\sum_{k=1}^{5} EI_k} \right\}$$

$$= \left\{ \frac{6\times 0.25 + 7\times 0.22 + ... + 6\times 0.15}{0.25 + 0.22 + ... + 0.15}, ..., \frac{8\times 0.25 + 9\times 0.22 + ... + 8\times 0.15}{0.25 + 0.22 + ... + 0.15} \right\}$$

$$= \{6.22, 7.22, 7.22, 8.22\}$$

where a_k, b_k, c_k and d_k are the four parameters in a converted UFN. All the aggregated UNFs are shown in Table 8-6.

Step 5: Calculating fuzzy WFs from comparison matrix.

Then, following steps 1 to 4 as described in Section 3.4.2.2, the entire comparison matrix for the hazard group can be developed. The comparison matrix M is then established with these aggregated UNFs according to Eq. 4-12.

$$M = \left[A_{i,j} \right] = \begin{bmatrix} A_{1,1} & A_{1,2} & \cdots & A_{1,7} \\ A_{2,1} & A_{2,2} & \cdots & A_{2,7} \\ \vdots & \vdots & \ddots & \vdots \\ A_{7,1} & A_{7,2} & \cdots & A_{7,7} \end{bmatrix}, i, j = 1, 2, \ldots, 7$$

$$= \begin{bmatrix} 1,1,1,1 & A_{1,2} & \cdots & A_{1,7} \\ A_{2,1} & 1,1,1,1 & \cdots & A_{2,7} \\ \vdots & \vdots & \ddots & \vdots \\ A_{7,1} & A_{7,2} & \cdots & 1,1,1,1 \end{bmatrix}.$$

By using propositions 3 and 4 as stated in Section 3.4.2.2, the entire comparison matrix can be obtained as shown in Table 8-7. For example, value $A_{1,4}$ is not in the interval [1/9,9], the following transformation functions must be applied:

$$f(x_a) = x_a^{1/\log_9^{108.11}}, f(x_b) = x_b^{1/\log_9^{108.11}}, f(x_c) = x_c^{1/\log_9^{108.11}}, f(x_d) = x_d^{1/\log_9^{108.11}}$$

Table 8-8 lists transferred entries that are used as the completed comparison matrix M.

The UFN geometric mean $\bar{A}_i$ of the *i*-th row in the comparison matrix is calculated by Eq. 4-13:

$$\bar{A}_1 = \left\{\bar{a}_1, \bar{b}_1, \bar{c}_1, \bar{d}_1\right\} = \left\{ \sqrt[6]{\prod_{j=1}^{6} a_{1,j}}, \sqrt[6]{\prod_{j=1}^{6} b_{1,j}}, \sqrt[6]{\prod_{j=1}^{6} c_{1,j}}, \sqrt[6]{\prod_{j=1}^{6} d_{1,j}} \right\}$$

$$= \left\{\sqrt[6]{1\times 2.36\times ...\times 1.01}, ..., \sqrt[6]{1\times 2.69\times ...\times 3.92}\right\} = \left\{1.992, 2.778, 2.778, 3.633\right\}$$

Similarly,

$$\bar{A}_2 = \{0.827, 1.099, 1.099, 1.382\}$$

$$\bar{A}_3 = \{0.452, 0.575, 0.575, 0.707\}$$

$$\bar{A}_4 = \{0.356, 0.443, 0.443, 0.558\}$$

$$\bar{A}_5 = \{0.790, 1.018, 1.018, 1.317\}$$

$$\bar{A}_6 = \{0.927, 1.264, 1.264, 1.976\}$$

Then fuzzy WFs W_i of hazard groups are calculated by Eq. 4-14.

$$W_1 = \left\{a_1, b_1, c_1, d_1\right\} = \left\{ \frac{\bar{a}_1}{\sum_{i=1}^{6} \bar{d}_i}, \frac{\bar{b}_1}{\sum_{i=1}^{6} \bar{c}_i}, \frac{\bar{c}_1}{\sum_{i=1}^{6} \bar{b}_i}, \frac{\bar{d}_1}{\sum_{i=1}^{6} \bar{a}_i} \right\}$$

$$= \left\{ \frac{1.992}{1.992 + 1.099 + ... + 0.927}, ..., \frac{3.633}{3.633 + 1.382 + ... + 1.976} \right\} = \left\{0.208, 0.387, 0.387, 0.680\right\}$$

Similarly,

$$W_2 = \left\{0.086, 0.153, 0.153, 0.259\right\}$$

$$W_3 = \left\{0.047, 0.080, 0.080, 0.132\right\}$$

$$W_4 = \left\{0.037, 0.062, 0.062, 0.104\right\}$$

$$W_5 = \left\{0.083, 0.142, 0.142, 0.247\right\}$$

$W_6 = \{0.097, 0.176, 0.176, 0.370\}$

Step 6: Defuzzification and normalisation.

The crisp value w_i' of fuzzy WF W_i can be calculated by Eq. 4-15.

$$w_1' = \frac{a_1 + 2(b_1 + c_1) + d_1}{6} = \frac{0.208 + 2 \times (0.387 + 0.387) + 0.680}{6} = 0.406$$

Similarly,

$w_2' = 0.160$

$w_3' = 0.083$

$w_4' = 0.065$

$w_5' = 0.149$

$w_6' = 0.195$

The final WFs of hazardous groups WF_i can be obtained by Eq. 4-16:

$$WF_1 = \frac{w_1'}{\sum_{i=1}^{6} w_1'} = \frac{0.406}{0.406 + 0.160 + ... + 0.195} = 0.48$$

Similarly,

$WF_2 = 0.10$

$WF_3 = 0.05$

$WF_4 = 0.03$

$WF_5 = 0.13$

$WF_6 = 0.21$

Step7: RLs and WFs synthesis.

Once the WFs of components are obtained, the RL of the “Track components” subsystem $RL_{Trackcomponents}$ can be derived from the synthesis of component WFs and using Eq. 4-17.

$$RL_{Trackcomponents} = \sum_{i=1}^{6} RL_i \cdot WF_i = 4.65 \times 0.48 + 4.00 \times 0.10 + ... + 4.22 \times 0.21 = 4.31$$

Similarly, on the basis of expert judgements on components of the “Foundation” subsystem, as shown in Table 8-9, and on subsystems of the “Track system”, as shown in Table 8-10, the RL of the “Foundation” subsystem $RL_{Foundation}$ can be derived from the synthesis of component WFs and by using Eqs. 6-1 and 6-2.

$$RL_{Foundation} = RL_{Formation} \cdot WF_{Formation} + RL_{Formation} \cdot WF_{Formation}$$
$$= 2.98 \times 0.65 + 3.28 \times 0.35 = 3.08$$

$$RL_{Tracksystem} = RL_{Foundation} \cdot WF_{Foundation} + RL_{Trackcomponent} \cdot WF_{Trackcomponent}$$
$$= 3.08 \times 0.17 + 4.31 \times 0.83 = 4.11$$

which indicates that the overall RL of “Track system” is 4.11 belonging to “Possible” with a belief of 100 percent.

Comparison	E1-(0.25)		E2-(0.22)		E3-(0.21)		E4-(0.17)		E5-(0.15)		Aggregated UFNs
	Judgment	UFNs	Judgment	UFNs	Judgment	UFNs	Judgment	UFNs	Judgment	UFNs	
Rail vs. Fishplate ($A_{1,2}$)	VI	6,7,7,8	7,8,9	7,8,8,9	6,7,8	6,7,7,8	VI	6,7,7,8	6-8	6,6,8,8	6.22,7.22,7.22,8.22
Fishplate vs.Fastening TfHG ($A_{2,3}$)	WI	2,3,3,4	4,5,6	4,5,5,6	4,5	4,4,5,5	WI	2,3,3,4	4,5	4,4,5,5	3.16,3.98,3.98,4.80
Fastening vs. Pad ($A_{3,4}$)	BEW& WI	1.5,2.5, 2.5,3.5	EQ	1,1,1,2	1,2,3	1,2,2,3	BEW& WI	1.5,2.5, 2.5,3.5	1,2,4	1,2,2,4	1.00,1.74,1.74,2.74
Ballast vs. Pad($A_{5,4}$)	SI	4,5,5,6	5,6,7	5,6,6,7	6,7,8	6,7,7,8	BSV&VI	5.5,6.5, 6.5,7.5	5,6,7,8	5,6,7,8	4.76,5.88,5.88,7.14
Sleeper vs. Ballast ($A_{6,5}$)	BEW& WI	1.5,2.5, 2.5,3.5	2,3,4	2,3,3,4	1,1,2	1,1,1,2	EQ	1,1,1,2	2,3,4	2,3,3,4	1.23,1.59,1.59,2.70

Table 8-6 Expert judgements for components of “Track Component” subsystem

$A_{i,j}$	1	2	3	4	5	6
1	1.00,1.00,1.00,1.00	6.22,7.22,7.22,8.22	19.66,28.74,28.74,39.46	19.66,50.00,50.00,108.11	2.75,8.50,8.50,22.70	1.02,5.35,5.35,18.39
2	0.12,0.14,0.14,0.16	1.00,1.00,1.00,1.00	3.16,3.98,3.98,4.80	3.16,6.93,6.93,13.15	0.44,1.18,1.18,2.76	0.16,0.74,0.74,2.24
3	0.025,0.03,0.03,0.05	0.20,0.25,0.25,0.32	1.00,1.00,1.00,1.00	1.00,1.74,1.74,2.74	0.14,0.30,0.30,0.58	0.05,0.19,0.19,0.47
4	9.25e-3,0.02,0.02,0.05	0.08,0.14,0.14,0.32	0.36,0.57,0.57,1.00	1.00,1.00,1.00,1.00	0.14,0.17,0.17,0.21	0.05,0.11,0.11,0.17
5	0.04,0.12,0.12,0.36	0.36,0.85,0.85,2.26	1.74,3.38,3.38,7.14	4.76,5.88,5.88,7.14	1.00,1.00,1.00,1.00	0.37,0.63,0.63,0.81
6	0.05,0.19,0.19,0.98	0.45,1.35,1.35,6.11	2.15,5.37,5.37,19.30	5.88,9.34,9.34,19.31	1.23,1.59,1.59,2.70	1.00,1.00,1.00,1.00

Table 8-7 Pairwise comparison matrix M established for track components

$A_{i,j}$	**1**	**2**	**3**	**4**	**5**	**6**
1	1.00,1.00,1.00,1.00	2.36,2.53,2.53,2.69	4.04,4.83,4.83,5.60	4.04,6.27,6.27,9.00	1.61,2.73,2.73,4.33	1.01,2.20,2.20,3.92
2	0.37,0.40,0.40,0.42	1.00,1.00,1.00,1.00	1.73,1.91,1.91,2.09	1.72,2.48,2.48,3.35	0.68,1.08,1.08,1.61	0.43,0.87,0.87,1.46
3	0.18,0.20,0.20,0.25	0.48,0.52,0.52,0.58	1.00,1.00,1.00,1.00	1.00,1.30,1.30,1.60	0.40,0.56,0.56,0.77	0.25,0.45,0.45,0.70
4	0.11,0.16,0.16,0.25	0.30,0.40,0.40,0.58	0.62,0.77,0.77,1.00	1.00,1.00,1.00,1.00	0.40,0.44,0.44,0.48	0.25,0.35,0.35,0.44
5	0.23,0.37,0.37,0.62	0.62,0.93,0.93,1.47	1.30,1.77,1.77,2.52	2.08,2.30,2.30,2.52	1.00,1.00,1.00,1.00	0.63,0.81,0.81,0.91
6	0.26,0.46,0.46,0.99	0.69,1.15,1.15,2.34	1.43,2.20,2.20,4.01	2.30,2.85,2.852,4.01	1.10,1.24,1.24,1.59	1.00,1.00,1.00,1.00

Table 8-8 Pairwise comparison matrix M established for track components

Compare	Formation layer	Base
Formation layer	1,1,1,1	BEW
Base		1,1,1,1

Table 8-9 Foundation comparison matrix

Compare	**Track Component**	**Foundation**
Track Component	1,1,1,1	BEW
Foundation		1,1,1,1

Table 8-10 Subsystem comparison matrix

8.3 Maintenance Option Decision Making

The input parameters are the FF, CP and CS of each failure mode. The RL of each failure mode is then assessed by using the FRA safety risk model. On the basis of the results of RLs of failure modes, the RLs of corresponding components are obtained by using a fuzzy aggregation operation as described in Section 6.3. The RLs of subsystems can then be derived by synthesizing the RLs of components and their corresponding weights. Finally, the RL of the track system can be obtained by Eq. 6-1. Table 8-11 shows the RLs of failure modes, components, subsystems and the overall RL of the track system with risk scores located from 0 to 10 and the defined risk categories of "*Low*", "*Possible*", "*Substantial*" and "*High*" with a belief of percentage. Table 8-11 also shows the percentages of risk contribution percentage (RC) of each component to subsystem and subsystem to the overall RL of the track system.

System	Subsystem	RL	RC	Component	RL	RC	Failure mode	RL
Track system (RL:4.11)	Track component	4.31	83%	Rail	4.65	52%	Defect	5
							Fatigue	5.50
							Poor support	3.58
							Damaged by powered wheel	3.80
				Fishplate	4.00	9%	Inadequately maintained rail joint support	4.00
				Fastening	4.00	5%	Clip wear	4.00
							Screw loose	4.00
				Pad	4.00	3%	Pad degradation	4.00
				Ballast	3.67	11%	Performance deterioration	3.67
				Sleeper	4.22	20%	Load damage	5.08
							Maintenance damage	3.10
	Subgrade	3.08	17%	Formation layer	2.98	63%	Load related failure	3.26
							Soil related failure	2.77
							Environment related failure	1.75
				Base	3.28	37%	Load related failure	3.75
							Soil related failure	2.75
							Environment related failure	1.75

Table 8-11 Results of risk assessment of track system

The RL of the overall system is 4.11. The RLs of the "*Track component*" subsystem and "*Subgrade*" subsystem are 4.31 and 3.08, respectively. It can be seen from Table 8-11 that the "*Track component"* subsystem is the major risk contributor that contributes 83% to the overall system RL, while the "*Subgrade*" subsystem contributes 17%. Within the "*Track component"* subsystem, the main risk contributions come from rail failures which contribute 52% to the RL of the subsystem. The "Rail", "Sleeper", "Ballast", "Fishplate", "Fastening" and "Pad" contribute 20%, 11%, 9%, 5% and 3% to the RL of the "*Track component*" subsystem, respectively.

Because the overall RL of the system is 4.11 belonging to the "Possible" category which falls in the transition region (e.g. "Possible" and "Substantial"). As described earlier in this thesis, if risks are in the transition region, they need to be reduced As Low As Reasonably Practicable (ALARP). Therefore, maintenance actions must be carried out to reduce RL of such a track system. Assume the safety requirement is that the overall RL of the system is no more than 3.00. The total maintenance budget is £750,000 and the detailed costs are shown in Table 8-12, which covers labour cost, equipment cost, materials and parts cost, and any other relevant costs. Suppose there are four maintenance options in hand. They are:

Option 1: Eliminating failure modes of "*Rail*", "*Fastening*", "*Pad*" and "*Ballast*" components by repair/renewal maintenance work.

Option 2: Eliminating failure modes of "*Rail*", "*Fastening*" and "*Ballast*" components by repair/renewal maintenance work.

Option 3: Eliminating failure modes of "*Rail*" and "*Ballast*" components by repair/renewal maintenance work.

Option 4: Eliminating failure modes of "*Rail*", "*Fishplate*", "*Fastening*", "*Pad*" and "*Sleeper*" by repair/renewal maintenance work.

System	**Subsystems**	**Components**	**RL**	**Repair/Renewal Cost (10^5 pounds)**
Track system	Track component	Rail	4.65	3.50
		Fishplate	4.00	2.00
		Fastening	4.00	0.07
		Pad	4.00	0.40
		Ballast	3.67	3.00
		Sleeper	4.22	1.10
	Subgrade	Formation layer	2.98	2.00
		Base	3.28	2.50

Table 8-12 Maintenance costs

Table 8-13 shows the cost of each maintenance option. The expected overall system RL after implementation of the corresponding maintenance option is re-assessed by using the proposed safety risk model as described in Section 3. As can be seen from Table 8-13, the RL of the overall track system has been reduced significantly, but the cost invested into each option is different. The proposed risk based maintenance decision making model can take into account risk and cost together to obtain the utility function associated with each option for ranking the maintenance options in hand; once all preference degrees of all maintenance options in hand are produced, the best option can be chosen. In this case, the best maintenance option can be determined by following the steps as described in Section 6.6.

Option	**Cost (10^5 pounds)**	**System RL**
Option 1	7.20	1.59
Option 2	6.70	1.69
Option 3	6.50	1.86
Option 4	5.60	2.35

Table 8-13 Costs of maintenance options and corresponding overall RL of the system

Based on the proposed cost-risk model, cost and risk values of these four options, derived from the risk model and the cost model are normalised and weighted.

By using Eqs. 6-16 and 6-17, the normalised cost of option 1 is calculated as

$$x_{1,\cos t} = \frac{Cost_1}{\sqrt{\sum_{i=1}^{4} Cost_1{}^2}} = \frac{7.2\times10^5}{\sqrt{\left(7.2\times10^5\right)^2+\left(6.7\times10^5\right)^2+\left(6.5\times10^5\right)^2+\left(5.6\times10^5\right)^2}} = 0.5517$$

and normalised system RL of option 1 is calculated as

$$x_{1,RL} = \frac{RL_1}{\sqrt{\sum_{i=1}^{4} {RL_1}^2}} = \frac{1.59}{\sqrt{1.59^2 + 1.69^2 + 1.86^2 + 2.35^2}} = 0.4195$$

As risk and cost are equally important in this case, the weighted normalised cost of option 1 is calculated as

$$y_{1,\cos t} = w_{\cos t} \cdot x_{1,\cos t} = 0.5 \times 0.5517 = 0.2758$$

and the weighted normalised system RL of option 1 is calculated as

$$y_{1,RL} = w_{RL} \cdot x_{1,RL} = 0.5 \times 0.4195 = 0.2097$$

Similarly, weighted normalised cost and system RL of the other options can be calculated as shown in Table 8-14 . According to Eqs. 6- 20 and 6-21, the best and worst scenario options can be defined as

$$A^+ = \{0.2145, 0.2097\}$$

and the worst scenario option is defined as

$$A^- = \{0.2758, 0.3100\}$$

By using these scenario options, according to Eqs. 6- 22, 6- 23 and 6-24, the preference degree of option 1 is calculated

$$D_1^{+} = \sqrt{\left(y_{1,\cos t} - y_{\cos t}^{+}\right)^2 + \left(y_{1,RL} - y_{RL}^{+}\right)^2} = \sqrt{(0.2758 - 0.2145)^2 + (0.2097 - 0.2097)^2} = 0.0613$$

$$D_1^{-} = \sqrt{\left(y_{1,\cos t} - y_{\cos t}^{-}\right)^2 + \left(y_{1,RL} - y_{RL}^{-}\right)^2} = \sqrt{(0.2758 - 0.2758)^2 + (0.2097 - 0.3100)^2} = 0.1103$$

$$P_1 = \frac{D_1^-}{D_1^+ + D_1^-} = \frac{0.1103}{0.0613 + 0.1103} = 0.6207$$

Option	$x_{i,\cos t}$	$y_{i,\cos t}$	$x_{i,RL}$	$y_{i,RL}$	D_i^+	D_i^-	P_i	Rank
Option 1	0.5517	0.2758	0.4195	0.2097	0.0613	0.1103	0.6207	2
Option 2	0.5134	0.2567	0.4459	0.2229	0.0442	0.0892	0.6688	1
Option 3	0.4980	0.2490	0.4907	0.2454	0.0496	0.0699	0.5849	3
Option 4	0.4291	0.2145	0.6200	0.3100	0.1003	0.0613	0.3793	4

Table 8-14 Results of preference evolution at each step

8.4 Results and Discussions

Obviously, option 2 is the best maintenance option because it has the highest preference degree with 66.88%. The results can also be demonstrated in Figure 8-3. Option 1 is the best safety maintenance option, but the cost appears too high. Option 4 is a low cost maintenance option, but the system risk appears too high. As can be seen from Figure 8-3, cost is increased with significant risk reduction from point 4 to point 1, which indicates that options 1, 2 and 3 are the potential “cost effective” options. Based on the proposed risk-cost model, the best option is the one with highest preference degree, which also indicates that it is the closest to the best scenario. Therefore, option 2 is the best maintenance option. If the maintenance work can be carried out based on option 2, the RL of the overall track system can be reduced from 4.11 (possible 100%) to 1.69 (low 100%), and cost would be £0.67 million which is within the budget.

8.4.1 Sensitive Analysis

A sensitive analysis has been carried out based on varying the repair/renewal cost of each component. Table 8-15 shows maintenance costs of components increased by 10% and 20%. Based on these variances, the cost of each maintenance option is calculated as shown in Table 8-16 and the calculated preference ranking of these maintenance options are summarised in Table 8-17.

Components	**RL**	**Repair/Renewal Cost (10^5 pounds)**	**Repair/Renewal Cost (10^5 pounds) +10%**	**Repair/Renewal Cost (10^5 pounds) +20%**
Rail	4.65	3.50	3.85	4.2
Fishplate	4.00	2.00	2.2	2.4
Fastening	4.00	0.07	0.077	0.084
Pad	4.00	0.40	0.44	0.48
Ballast	3.67	3.00	3.3	3.6
Sleeper	4.22	1.10	1.21	1.32
Formation layer	2.98	2.00	2.2	2.4
Base	3.28	2.50	2.75	3

Table 8-15 Maintenance cost increased by 10% and 20% for each component.

Option	**Original Cost (10^5 pounds)**	**Cost (10^5 pounds) +10%**	**Cost (10^5 pounds) +20%**	**System RL**
Option 1	7.20	7.92	8.64	1.59
Option 2	6.70	7.37	8.04	1.69
Option 3	6.50	7.15	7.8	1.86
Option 4	5.60	6.16	6.72	2.35

Table 8-16 Costs of maintenance options and corresponding overall RL of the system according to component cost variances by 10% and 20%

Option	**Original** P_i	Cost +10% P_i	Cost +20% P_i	Rank
Option 1	0.6207	0.6207	0.6207	2
Option 2	0.6688	0.6688	0.6688	1
Option 3	0.5849	0.5849	0.5849	3
Option 4	0.3793	0.3793	0.3793	4

Table 8-17 Preference ranking based on varying maintenance costs.

The results show that the proposed cost-risk model is not sensitive to the variance of the cost of each component as it will not affect the preference degrees of maintenance options. However, it is obviously very sensitive to risk contributions of risk contributions of components and subsystems as shown in Table 8-11, as the RL of overall system will be significantly reduced when high risk contributors are eliminated. As the inputs of risk-cost model are the combinations of maintenance options, the combination of each option will also significantly affect the results.

From this case, it is obvious that the proposed risk based decision making model can assist the asset management team in understanding the problem and making an effective decision as to what risk reduction measures should be taken.

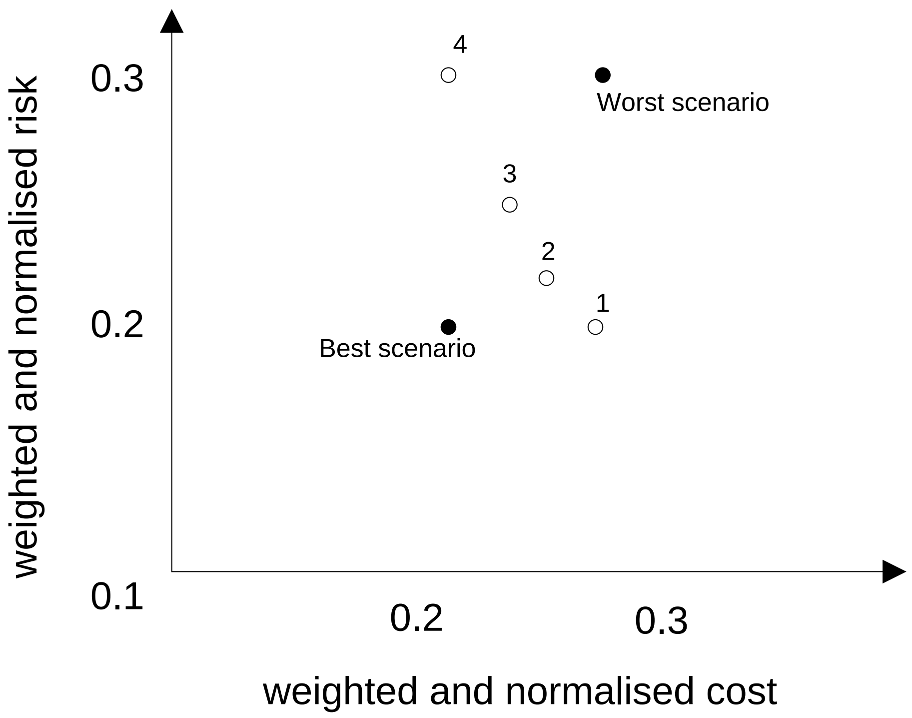


Figure 8-3 Four maintenance options

8.5 Summary

This chapter presents a case study on the risk assessment of a track system using the proposed risk-based maintenance decision making model, which incorporates safety risk and cost into the railway maintenance process to make maintenance decisions for railway systems. The proposed risk-based maintenance decision making system provides railway engineers, operators, managers and maintainers with a useful method and tool to make full use of the information produced from safety risk and cost analysis and to take into consideration maintenance aspects simultaneously. Great benefits may be received by using the proposed risk-cost modelling methodology into the railway maintenance process, so that maintenance work can be made more economically while system safety is improved. The proposed risk-based maintenance decision making system can also be used to assist engineers and risk analysts in understanding the interaction between safety and cost considerations, so as to balance the best utilisation of resources for maintaining railway systems.

CHAPTER 9: CONCLUSIONS AND RECOMMENDATIONS

9.1 Conclusions

The research has achieved its main goal of improving railway safety by developing safety risk models and tools using FRA and AHP techniques for railway safety risk assessment processes. The research has proved that the proposed risk model can successfully help rail vehicles, infrastructure operators, track & civil engineering designers and maintainers, and health & safety advisors to improve railway safety through design, diagnosis and maintenance of railway systems. The achievements of this research can be summarised as follows:

- The objective of investigation of railway safety risk assessment tools as used in practice and in research literature worldwide has been achieved. This has been accomplished through conducting an extensive literature review of railway safety risk assessment techniques which highlights railway safety concepts and discusses the implementations and applications of current risk assessment techniques in railways. It was found that current techniques applied in railway safety risk assessment may not be appropriate when there is a high level of uncertainty involved in the risk data and information. The application of FRA and Fuzzy-AHP in the risk model may solve such a problem. This research also introduces a new parameter of 'consequence probability' in the risk assessment process, which enhances the risk analysis.
- The objective of development of railway safety risk models and tools to facilitate railway safety risk analysis has been achieved. Safety risk models based on FRA combined with improved Fuzzy-AHP technique have been established for processing safety risk assessment efficiently and effectively. By introducing the parameter of 'consequence probability', it distinguishes a hazard event with a higher

probability of consequence to cause fatalities. This will affect the overall risk ranking and finally affect the decision making of potential safety measures or maintenance strategies. Also by the application of improved Fuzzy-AHP, the required number of expert judgements is reduced from $n(n-1)/2$ to $n-1$ when conducting pairwise comparison. It is a significant advantage to compare with the traditional method when the number of involved alternatives n is high. The other advantage of applying improved fuzzy-AHP is that the comparison matrix derived from expert judgements is always consistent, while the consistency test is needed in traditional fuzzy-AHP. Therefore, the proposed model can produce much more reliable results than other risk assessment techniques.

- The objective of validation of the proposed railway safety risk system via case studies with the industrial partners has been achieved. The case studies on risk assessment of shunting at Hammersmith and a track system are used to validate the proposed models, and relevant papers have been published. The proposed model can provide detailed results, which include risk contributions arising at system level, sub-system level as well as component level, and also include RLs in the format of risk score and risk categories with a degree of confidence.
- The objective of developing advanced risk-cost model to assist maintenance decision making process has been achieved. TOPSIS, one of the multi-objective decision-making techniques, has been employed to select the best solution for railway maintenance decision making. This model combines a risk model with a cost model to be developed into a cost benefit based risk decision making tool. It can provide decision makers with a ranking of maintenance options or strategies in terms of preference degrees. A relevant paper has been accepted and will be published soon.
- The objective of application of the proposed methodology and tool to railway maintenance decision making has been achieved. The developed software based on the proposed risk models, namely RISRAS, has been delivered to railway industry with the user manual, and workshops have been organised to deliver research results to the industry.

Innovative features of this research are emphasised as follows:

Innovation 1:

The proposed railway safety risk model is developed based on FRA and fuzzy-AHP approaches, where the potential risk to railway operations is assessed in terms of four parameters, i.e. FF, CP, CS and WF. It is quite appropriate for the circumstance where some risk events frequently happen and may possibly lead to serious consequences depending on the existing risk control measures. It is worth noting that by using four parameters could help risk analysts with likelihood analysis and even with risk control measures that are designed to reduce the likelihood aspect of risk, since the CP is introduced in the assessment. More risk information, such as frequency and probability, which can be derived either from expert judgements or past records, can be directly used in the risk estimation. Finally, this will affect the overall risk ranking, so that the hazard event with very high occurrence frequency but very low consequence probability or with very low occurrence frequency but very high consequence probability can be identified.

Innovation 2

In any cases, if no existing risk data and information available, subjective estimations can be used in the proposed risk analysis modules. The proposed railway safety risk model allows vague and imprecise descriptors such as "*likely*" and "*impossible*" to be used directly to capture expert judgements and it also provides a flexible method of combining the opinions of experts with various experiences from different backgrounds.

Innovation 3

Improved Fuzzy- AHP is employed for the risk assessment, which only requires few judgements from experts without any consistency test. This will reduce the complexity of the application of Fuzzy-AHP.

Innovation 4

The development of software based on the proposed risk model is designed especially for railways. Compared to other tools, the advantages of the developed software can be summarised as follows:

- It can combine expert knowledge and engineering judgments with other risk historical data for the railway safety and risk assessment in a consistent manner;
- It can deal with imprecise, ambiguous, incomplete and uncertain information in the assessment;
- It can apply linguistic expressions directly to the risk assessment;
- It can provide a flexible structure for risk analysis.

Innovation 5

The risk-based decision making module that combines the proposed safety risk model and a cost model, has been developed for maintenance option decision making. By using this model, preference degrees of maintenance options can be determined in which risk reduction and cost are taken into consideration. The results from the system can demonstrate that the maintenance option with the highest preference degree can reduce the RL of the system as low as reasonably practicable.

9.2 Recommendations for Future Work

Every research study has its own intrinsic limitations and weaknesses. Some future work can be anticipated and is summarised on the basis of current research. Firstly, as the third parametre CP has been introduced in the current risk model, the rulebase of the model has become bigger. It may be difficult to design the rulebase when parametres have many linguistic terms, and experts may need to input and design hundreds of rules . Hence, it is still worth carrying out further study to identify effective solution, such as an additional software, to facilitate the design of rulebase.

Secondly, the software based on the proposed model has already been developed. However, it still needs to be further improved based on the feedback from industrial users, so that the assessment process can be facilitated.

Finally, risk-based decision making model has been developed, and it should be integrated with the developed software (RISRAS) in the future, and more case studies should be conducted based on the application of the developed software.

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