A Function Allocation Framework for the Automation of Railway Maintenance Practices

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ABSTRACT

The railway industry has seen significant innovation in intelligent maintenance systems leading to improvements in efficiency and reliability. However, ongoing challenges such as intensity of labour, hazardous environments, and operational inefficiency necessitate advancement in the deployment of Robotic and Autonomous Systems (RAS). Successful implementation of RAS in a railway context requires a comprehensive function allocation process. This thesis presents a novel function allocation framework for systematic task analysis and allocation. The framework includes comprehensive multi-stage evaluation criteria such as technical feasibility, overall system performance, and cost impact. Function allocation for each identified subtask is realised in an iterative manner to reach a final system design, and the structure and elements of the framework are supported by rigorous derivations and practical examples. The proposed framework has been successfully applied and thoroughly demonstrated through case studies based around the maintenance activities of wheelsets. The case studies demonstrate that the proposed framework is capable of providing guidance in system design at the preliminary stages of the introduction of automation into railway maintenance systems; also, can help to re-evaluate an already implemented system and thus propose guidance on whether the current allocation can be optimised.

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LIST OF ABBREVIATIONS

Term	Explanation/Meaning/Definition
ACEM-Rail	Automated and Cost-Efficient Maintenance for Railway
ACFM	Alternating Current Field Measurement
AHP	Analytic Hierarchy Process
ATO	Automatic Train Operation
BCRRE	Birmingham Centre for Railway Research and Education
CBA	Cost-benefit Analysis
CSM RA	Common Safety Method for Risk Evaluation and Assessment
ELECTRE	Elimination and Choice Expressing and Reality
EMATs	Electromagnetic Acoustic Transducers
EPC	Error Producing Conditions
FMEA	Failure Modes and Effects Analysis
FTA	Fault Tree Analysis
GTT	Generic Task Type
GRIP	Governance for Railway Investment Projects
HEP	Human Error Probability
ICT	Inter City Express

LCC	Life Cycle Cost
LOAs	Levels of Automation
MABA-MABA	Men Are Better At/Machines Are Better At
MCDM	Multi-Criteria Decision-Making
MFL	Magnetic Flux Leakage
MPI	Maintenance Performance Indicator
MTBF	Mean Time Between Failure
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NDI	Non-destructive Inspection
NDT	Non-destructive Testing
ORR	Office of Rail and Road
PAUT	Phased Array Ultrasonic Testing
PLPR	Plain Line Pattern Recognition
RAM	Reliability Availability Maintainability
RAM-LCC	Reliability Availability Maintainability and Life Cycle Cost
RAMS	Reliability, Availability, Maintainability and Safety
RARA	Railway Action Reliability Assessment
RAS	Robotics and Autonomous Systems
RBD	Reliability Block Diagram
RCF	Rolling Contact Fatigue

RFI	Rete Ferroviaria Italiana
RRUKA	Rail Research UK Association
RSSB	Rail Safety and Standards Board
RTS	Rail Technical Strategy
SE	Systems Engineering
SIMO	Simultaneous Motion
TOC	Train Operating Company
TRL	Technology Readiness Level
VISyR	Visual Inspection System for Railway
VMIs	Vehicle Maintenance Instruments

CHAPTER 1 INTRODUCTION AND BACKGROUND

1.1 Current railway maintenance in the UK

The railway plays a crucial role in the modern public transport system. According to Transport Statistics Great Britain 2018 [1], in 2017/2018, more than 17 billion tonne-kilometres of freight were moved by rail in Great Britain, and approximately 1.71 billion passenger journeys were made by National Rail, a significant increase of 149% since 1985/86 which saw the largest share of passenger-kilometres. Furthermore, there were 0.27 billion passenger journeys on light rail and tram systems in the same year.

Nowadays, the British railway is one of the busiest railway systems; according to the data collected by Network Rail in 2010, UK railway systems run almost 20% more trains than France, and more than Spain, Switzerland, the Netherlands, Portugal and Norway [2]. However, it is the oldest in the world, with the first public railway opened in 1803 [3]. With the large number of operating trains and passengers, the demand for railway services has been increasing. For example, M. Wardman and G. Whelan [4] stated that commuter trains in London and the South East are overcrowded at peak times.

In order to assure its capacity to meet rail traffic demand, both railway infrastructure and rolling stock should be well maintained. Maintenance is an essential element in ensuring reliable and safe operation, which helps improve railway availability and system efficiency [5][6]. Nowadays, railway researchers and engineers worldwide have been proposing numerous innovations to optimise maintenance solutions, aiming to deliver more reliable, cost-efficient and intelligent railway maintenance systems. For example, by applying information and communications technology, the Research and Development Centre of the Japan Rail East Group has proposed the 'Smart Maintenance Initiative', a platform with an integrated database to aid asset management decisions, which has been tested on the Keihin–Tohoko Line [7]. A real-time automatic inspection system for detection of worn and missing fasteners has been implemented based on computer vison [8]. Supported by the European Commission, a recent research project called Automated and Cost Efficient Maintenance for Railway (ACEM-Rail) is aiming to development an automatic, intelligent maintenance management system with the intention of increasing the availability, quality and reliability, and reducing the cost of maintenance [9].

Despite the growing pace of maintenance innovation, many challenges remain. The Rail Research UK Association (RRUKA), which evolved from a partnership between UK universities to address railway research following privatisation of the industry, summarised the following key challenges [10]:

- Currently, railway maintenance procedures still rely mainly on humans. Although no one intends to make a mistake, psychology research indicates that human beings are inevitably vulnerable to errors from time to time.
- Railway maintenance is particularly prone to errors due to system complexity. Maintenance technicians often get involved in frequent disassembly, inspection and replacement of various components. Maintenance requires a high level of vigilance and skills to detect faults.
- Certain railway maintenance tasks are performed in a hazardous environment as well as under time pressure.

Above all, modern railway maintenance practices are facing major challenges including human performance issues, labour intensity, time pressure and potential hazards. To seek strategies to deal with existing challenges, Network Rail published a series of challenge statements to raise industrial awareness and encourage innovation [11].

The related document identifies a need for maintenance as follows:

- Enabling transition to predict and prevent maintenance regimes;
- Automating inspection and maintenance activities to remove the workforce from high-risk areas and improve data capture.

It can be seen that Network Rail considers the development of automated systems and introduction of more predictive/preventive maintenance as the solutions to improve current maintenance practices.

Similarly, the Rail Safety and Standards Board (RSSB) published the Rail Technical Strategy (RTS) in 2012 [12], which is the industry's vision of a modernised railway of the future; as part of the Capability Delivery Plan, it identifies that the application of robotics and autonomous systems (RAS) would minimise hazards to railway staff as well as being a potential step towards the maintenance revolution.

RAS has been used as a smarter solution applied in various industries where the tasks fall into the '4Ds' category: 'dangerous, difficult, dirty and dull' [13]. For example, in manufacturing pipelines, it is used for handling, welding and assembly [14]; correspondingly, there are lots of heavy loadings and dangerous operations in a railway depot that RAS may assist. RAS is also practically useful in some surgical procedures nowadays [15], which indicates that it has the potential to deal with various delicate components on trains.

It can be suggested that RAS may be beneficial for the transport industry to replace or assist humans in dangerous (hazardous and hard to access) working conditions and monotonous repetitive routines. As a result, current maintenance capacity, efficiency and overall safety would be greatly enhanced.

The scope of this research only includes the analysis of rolling stock maintenance. Railway assets mainly consist of rolling stock and infrastructure. So far, there have been intensive studies focusing on infrastructure assets, for example tracks, electrical units and signalling systems, but less research around rolling stock. In fact, rolling stock is the one of the most maintenance-intensive parts of the railway system. If maintenance is neglected, a rolling stock failure may cause delays, train service disruption and even derailment [16].

1.2 Challenges of automating railway maintenance and function allocation

RAS has proven to be a potential tool to achieve better maintenance performance and further improve railway availability. However, the current railway maintenance system only sees a few of these advantages due to practical difficulties. This section gives an overview of the challenges of automating the process.

Firstly, railway maintenance systems are complex, composing of many sub-systems that interact with each other; a change in one small process may affect all subsequent tasks [17]. B. S. Blanchard and W. J. Fabryky [18] demonstrated that as the complexity of systems is increasing, there is a trend that many of those systems may not meet the requirements of users in terms of performance, effectiveness and overall cost.

Secondly, RAS normally works in a structured environment where surroundings are constrained to adapt to the capabilities of the autonomous systems [19], while for railway maintenance, RAS has to work in an environment with various uncertainties; operating in such an environment poses critical challenges (which are further discussed in Chapter 4.1).

Besides that, emerging technologies are normally expensive, in addition to the initial investment, operating costs, maintenance costs and time/money for staff training are also overheads which cannot be neglected. As a result, the innovations and technologies are hard to implement despite injecting greater competition into the rail industry.

Furthermore, RAS and humans have their own strengths, and there is a need to compare the performance of RAS and humans, respectively, during the preliminary system design stage.

Finally, automation is always associated with human factors. R. Parasuraman and V. Riley [20] pointed out that excessive automation may lead to enhancement of human dependency and a skills decline. Overreliance on automation can result in failures of system monitoring and decision bias. Especially for a safety-critical industry, human trust in automation is the major issue affecting usage [21].Trust develops rapidly if automation is highly reliable; however, Lee and Moray [22] found that humans' trust of automation is slow to recover once a failure occurs. In summary, the technical feasibility, economic factors, existing system performance and consequences of human performance all need to be considered when implementing RAS. Proper system design should address all of these issues, to meet the requirements of different stakeholders.

In a RAS system, decisions about which functions are to be done manually and which functions will be automated will have a direct impact on the system's operational mechanisms. Therefore, it is essential to decide what function should be automated and to what extent, which is the definition of 'function allocation' in this thesis.

The term 'function' has been defined differently in different fields of study. In human–machine interaction studies, Dearden defined 'function' as the activities that the integrated human–machine system is required to be capable of performing [23]. Some other authors prefer to use the terms 'task' and 'function' interchangeably [24][25][26]. This thesis retains Dearden's definition, and the term 'task' is equivalent to 'function'.

In human–machine systems, function allocation is the consideration of the respective human–machine capabilities, experiences, scientific principles and some reality constraints [24]. Figure 1.1 [27] presents a typical example of the classic human–machine system model. It is a loop of information exchange process among humans, machines, interactive user interface and the surrounding environment, ultimately leading to task completion. In this loop, information is transmitted from the machine to the human via a display, and from the human to the machine through a control device. The boundary defines what components are considered within the scope of the system. It can be seen that environment is also considered as part of the human–machine system. In a human-machine system, the respective human–machine capabilities, experience, scientific principles and reality constraints are taken into account[28]. A review of existing function allocation theories is demonstrated in Chapter 2.

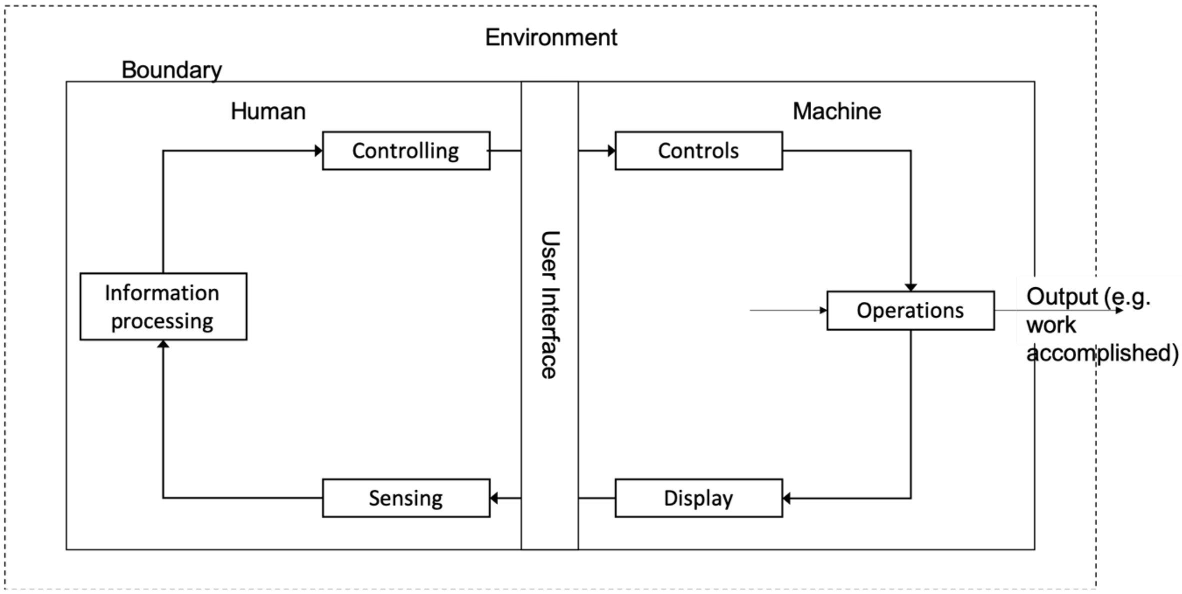


Figure 1.1 Human–machine system [27]

Function allocation is a core activity at the early stages of human–machine system design. H. E. Price et al. [29] pointed out that a proper function allocation is very important at the early stage of system development. Especially given the fact that the railway is a highly regulated industry, the intention of using RAS would theoretically improve maintenance effectiveness, freeing technicians from monotonous and dangerous tasks and thus improving reliability. In the meantime, the impact of regulatory challenges, standard changes, test rig development, technically acceptable levels, the safety issues of RAS, and staff skill development are essential factors to overcome [30]. Once the allocation completed, it will have only a limited effect on the following design activities; therefore, a poor allocation or the inappropriate use of automation is difficult and costly to rectify. Hence, the function allocation problem needs to be considered carefully and comprehensively.

Currently, there is lack of research in the decision-making regime applied in railway maintenance systems. With the intention to help designers efficiently determine the tasks to be automated within the railway maintenance system, a comprehensive function allocation framework is required.

1.3 Research hypothesis, aims and objectives

The hypothesis of this research is:

With appropriate function allocation decisions, the application of RAS could help the rail industry to improve rolling stock maintenance practice.

The aim of this research is to present a novel methodology, which helps decision-making in function allocation for the investigation of railway maintenance automation solutions.

The objectives associated with this aim are:

a) To identify the current railway maintenance environment, maintenance processes and maintenance challenges and how RAS can assist.
b) To identify the evaluation criteria for rolling stock maintenance systems.
c) To study how practical it is for RAS to be implemented in a rolling stock depot, it is important to review existing railway RAS applications as well as existing automated manipulation systems.
d) To identify existing function allocation theories in other industries and how these could be transferred to railway practices.
e) To develop and demonstrate a novel framework to support decision-making in railway maintenance function allocation.

1.4 Thesis structure

This thesis is structured as follows:

Chapter 1 provides background introduction and the research motivation of this thesis.

Chapter 2 outlines railway maintenance activities, categories and demands. Next, a brief introduction to RAS is given, followed by a review of the current implementation of railway RAS applications. Then, current function allocation methods are reviewed.

Chapter 3 includes a review of the decision-making process used for complex systems. A multi-criteria decision-making example is presented. The methodology presented in this chapter will support the function allocation decision (Chapter 5) and case study (Chapter 6).

Chapter 4 discusses how the decision-making methods could be applied to railway maintenance; elaborations of decision-making criteria and alternatives are included.

Chapter 5 brings together the theory of novel railway maintenance function allocation frameworks.

Chapter 6 demonstrates how the framework can be applied, with an automated robotic wheelset inspection case study and a wheel lathe case study.

Chapter 7 draws conclusions of this thesis with major contributions of a novel function allocation framework as well as presenting a railway RAS application. Limitations and further suggestions are given for future extension of the research.

CHAPTER 2 LITERATURE REVIEW

This chapter gives an introduction to the elements which need to be considered when designing an automated railway maintenance system, including the railway maintenance regime, railway automation application review, the current development of robotics and autonomous systems (RAS) and a perspective on future development. Then, the literature review of function allocation lays the theoretical foundation for the present research work.

Section 2.1 presents an overview of the current state of railway maintenance practices, starting with general maintenance across all domains then narrowing into railway maintenance activities. Section 2.2 introduces preventive maintenance with the example of Tokaido Shinkansen rolling stock maintenance. Section 2.3 outlines the features of NDT methods. Maintenance demands and future needs are summarised in 2.4. Section 2.5 explores the research undertaken in the area of automated railway maintenance and NDT automation. Function allocation theories are reviewed and discussed in section 2.6, which also comments on their advantages and disadvantages, together with the unique issues in the railway context.

2.1 Maintenance categories and activities

One of the definitions of maintenance from the Oxford Advanced Learner's Dictionary is 'the act of keeping something in good condition by checking or repairing it regularly'. Moubray, in the book *Reliability-Centred Maintenance*, defines maintenance as 'ensuring that physical assets continue to do what their users want them to do' [31]. In other words, maintenance is a series of activities necessary for assets or systems to keep an operational status.

As illustrated in Figure 2.1, based on whether maintenance activities are carried out before or after a fault has been detected, the European standard EN 13306 divides maintenance activities into corrective and preventive types. While the former aims to repair the system after breakdowns, the latter is commonly performed before a failure occurs, typically at predetermined intervals or when prescribed criteria are met, to prevent an item from failing. Then, according to how the maintenance interval is determined, preventive maintenance activities are further categorised as condition-based or predetermined [32].

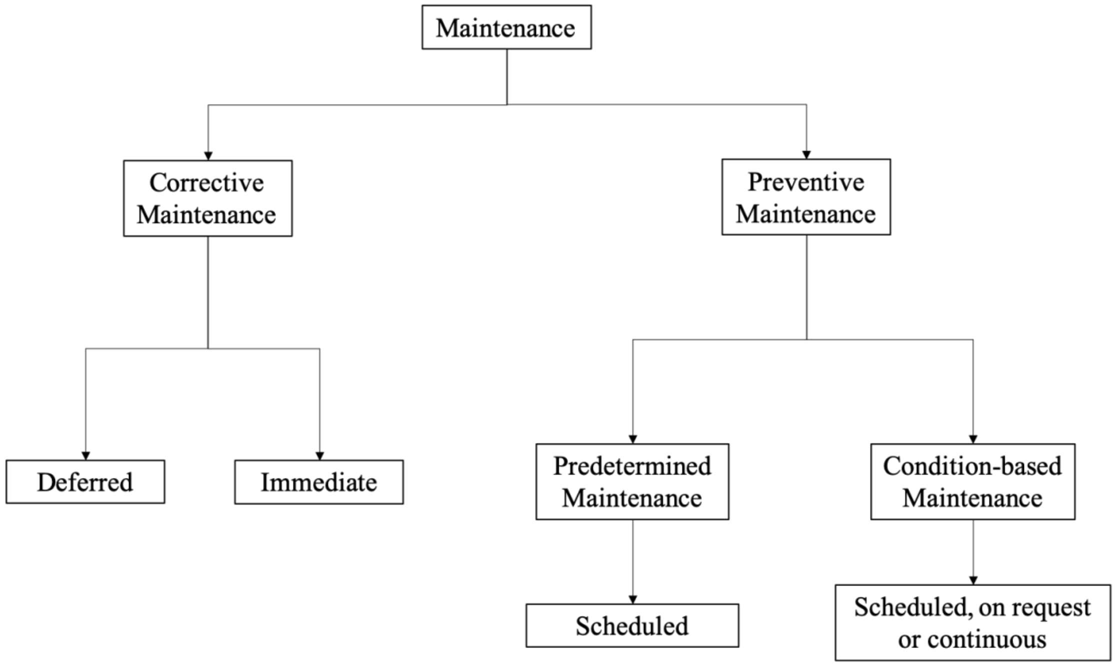


Figure 2.1 Maintenance task categories[32]

Safety is paramount for railway systems; therefore, despite corrective actions still existing in railway maintenance, it is inherently not appropriate for safety-critical railway components. Instead, undertaking enough preventive maintenance is essential to avoid any disasters. Thus, corrective maintenance is not the primary focus of this study.

Condition-based maintenance predicts failures before they occur, to prevent railway asset breakdown and to ensure that trains operate properly throughout their service time [33]. There are already a number of automated systems employed in condition monitoring. For example, the development of networking technologies allows vast numbers of distributed sensors to be networked, to automate and constantly monitor the environment and conditions of machines and systems [34]. Researchers have proposed sophisticated algorithms to aid decision-making when the historical maintenance data is uncertain or incomplete for predictions. For instance, R. Rippen et al. [35] summarised that artificial intelligence systems such as Bayesian statistics and generic algorithms have been used for decision support. It can be noted that condition-based processes are inherently reliant on computers or intelligent systems to assist with data acquisition, processing and prediction.

In a railway maintenance depot, the most common activities are periodic maintenance, and it is rarely automated. Introducing automation into a rolling stock depot is a topic worth investigating. As a result, the present study will focus on periodic maintenance.

2.2 Preventive maintenance

In railway practices, maintenance intervals can be at a predetermined time or distance, also known as time-based maintenance and distance-based maintenance, respectively. The time-based solution is ideal for those age-related failure modes such as fatigue, corrosion, oxidation and evaporation. By contrast, distance-based maintenance targets distance-related failure, for example, wheel flats and rolling contact fatigue cracks [36].

The major maintenance activities in a depot comprise inspection, condition monitoring, routine maintenance and overhaul. These terminologies are defined in EN 13306:2010 as follows [32]:

Inspection is interpreted as ‘examination for conformity by measuring, observing or testing the relevant characteristics of an item’.

Condition monitoring is the activity performed either manually or automatically which aims to measure the actual state of an item at predetermined intervals. Condition monitoring is used to evaluate any changes in the parameters of the item over time and is usually carried out in the operating state.

Routine maintenance describes regular or repeated simple preventive maintenance activities. It may involve cleaning, replacement of components, or small repairs.

Overhaul is a comprehensive set of preventive maintenance activities intended to maintain the required performance level of an item. It can be carried out at prescribed intervals of time or number of operations. It may also require partial or complete dismantling of an item.

To illustrate the typical maintenance regime adopted by a train operating company (TOC), the Shinkansen rolling stock maintenance management schedule is used as an example here [37]. Shinkansen is a massive network of high-speed (up to 320 km/h) lines operated by the Japan Railways Group, one of the busiest high-speed rail lines worldwide. According to the International High-Speed Rail Association[38], in 2017, the original Shinkansen carried 159 million passengers. Thus, it is critical to have a well-planned maintenance regime.

As shown in Figure 2.2, there are four types of periodic maintenance activities carried out in Tokaido Shinkansen maintenance:

- The **pre-service inspection** is normally visual, commencing prior to operation. It is generally conducted every 48 hours, during which there is routine examination of wheels, brakes and pantographs; inspections mainly take place during the night or in the early morning. Maintenance technicians visually inspect each component to determine its status. Once any abnormalities are indicated, the train cannot operate until the problems are identified and corrected.
- Every 45 days, a **regular inspection** is done, during which components not easily seen from the outside are carefully inspected. It is not adequate to assess the condition of a component by visual inspection alone during a regular inspection. For instance, certain small defects (i.e. < 5 mm) or inner defects can be missed [39]. Many non-destructive

inspection (NDI) methods have been used extensively for railway regular inspection. In these scenarios, components are still installed in the vehicle where it is often hard for humans to reach. Some components are designed to be hollow inside to allow insertion of NDI equipment without disassembly. Furthermore, this design makes the train lighter. One example of in-service inspection is the ultrasonic shaft test, which uses an ultrasonic probe on the axle end after removal of the axle end-cap while retaining the bearing on the axle [40].

- The third stage is the **bogie inspection**, conducted every 18 months. The bogies are critical components of the train. They are disassembled and rotated to ensure a thorough inspection.

- The fourth stage is the **general overhaul**, performed at a 1.2 million-kilometre interval or every 3 years, whichever comes first. The bogies, wheels and even the passenger seats are disassembled, inspected and overhauled. It also includes a complete repainting, and afterwards the train returns to service as a brand-new vehicle. NDI is also involved in the overhaul to give a thorough examination to identify defects and repair needs.

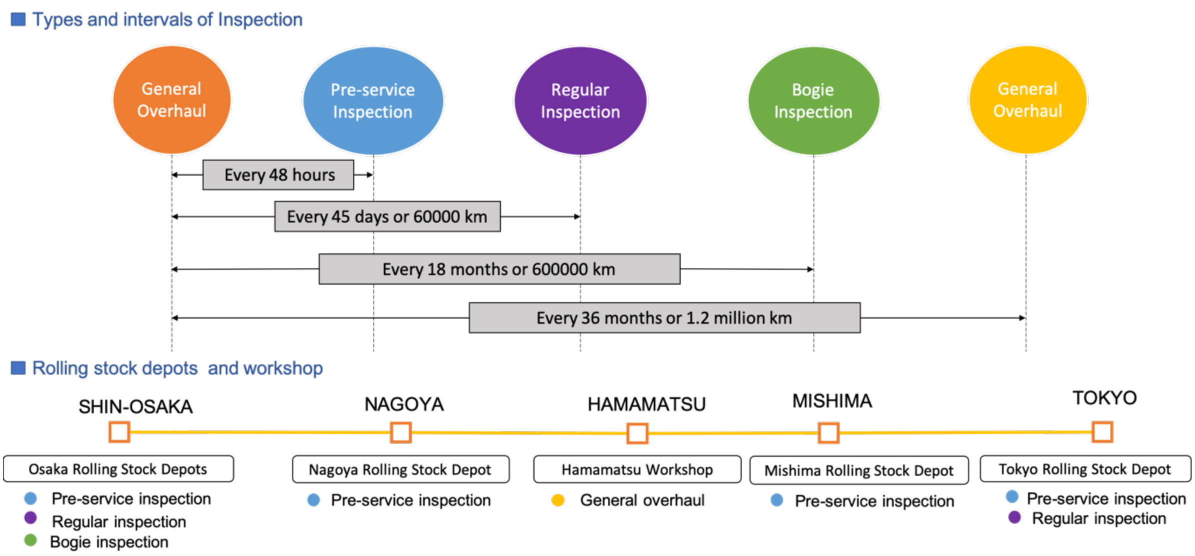


Figure 2.2 Maintenance management of Shinkansen rolling stock[38]

2.3 Non-destructive inspection (NDI) methods in railway maintenance

It can be noted that NDI has been frequently adopted for diverse maintenance activities.

A comprehensive understanding of NDI and its current stage of application for automation will assist this study in making decisions about automated inspection. Thus, this section reviews the NDI methods and includes its common applications, advantages and disadvantages and the feasibility of being automated.

2.3.1 Visual inspection

Visual inspection is the most widely used method among NDI due to its ease of application and fast execution time. Therefore, it is usually performed before applying other NDT methods since a simple visual examination can reveal surface defects, helping to make an immediate decision of a rejection or further inspection. Hence, it saves significant time and cost which would have been wasted by using more complicated testing procedures [41].

In fact, the most valuable tool for visual inspection is the human eye. Even without any optical aids, it can sense the change of lighting properties after contact with an inspection object and has sensitive visual perception. A well-trained technician can identify, for example, general condition, corrosion and defects on the surface, or some mechanical faults like sharp notches.

Although the human eye is useful, there are challenges: visual inspection is time-consuming and decreases inspection quality and employee morale with an increasing number of samples, and training costs are high. Hou, Lin and Drury [42] have demonstrated that the inspection combining human, sensor and control console would typically deliver better performance than only replying on one of them. With the advancement of machine vision, visual inspection systems are becoming more intelligent. Image processing, pattern recognition and automatic accept/reject choices are used when assessing a large number of components.

The number of machine vision applications has been increasing during recent years. In RAS, machine/robot vision refers to the ability to visually perceive the surrounding environment's information then aid in the execution of different types of task. For example, a robot is initially 'blind'; robot vision is widely used for robotic environment navigation and obstacle avoidance [43]. Developed by Network Rail, PLPR (plain line pattern recognition) is a facility used to detect clips missing from track sleepers. The vision system uses high-speed cameras to record raw images at a high frequency, then the data is processed using vison software. PLPR has improved the accuracy and frequency of inspections; it also provides a safer method of inspection and, as of 2019, it has replaced manual inspections on 8500 miles of track [44].

Apart from RAS and railway engineering, automated visual systems are also applied in agriculture for handling, inspection and packing of fruit and vegetables [45], and for personnel verification based on automated iris recognition for non-invasive biometric measurement [46].

2.3.2 Review of other NDI methods

After visual inspection, other NDI methods are usually used for a more thorough examination, particularly for safety-critical components such as wheels and axles. One of the common approaches is ultrasonic phased arrays, which are reliable [47]. Despite their reliability, ultrasonic phased arrays may still miss small surface-breaking defects, leading to catastrophic failure. As a result, magnetic flux leakage (MFL), eddy current testing and Alternating Current Field Measurement (ACFM) are commonly used, complementary to ultrasonic inspection [41]. A typical example is from the SAFERAIL project which aims to minimise wheelset failures and damage caused by wheel flats, shells and cracks. Researchers proposed to develop a new platform combining ultrasonic phased arrays with ACFM sensors for faster and more reliable inspection of wheelsets [48]. Table 2-1 reviews the common NDI techniques.

Table 2-1 NDI methods [49]

NDI method	Benefits	Limitations
Ultrasonic testing	Extremely good for detecting internal flaws within the body of the rail.	Has problems in finding small defects that initiate at the surface of the rail.
Eddy current testing	There is no need for mechanical contact with the test piece.	Only applicable for detecting surface and near-surface flaws.
Magnetic flux leakage (MFL)	Particularly good at detecting near-surface or surface transverse defects, such as RCF cracking.	Deep internal cracks are not detected with MFL methods. Adversely affected by increasing the speed at which the inspection takes place.
Long-range ultrasonic (guided waves)	Can be effective over long distances (up to 180 m).	Defects are very likely to be missed during inspection.
Laser ultrasonic	Remote implementation of a conventional ultrasonic inspection system.	It must be noted that the reflected laser beam is not shadowed and therefore cannot strike the receiving array.
Alternating current field measurement (ACFM)	High inspection speed. The extension of sizing models to accommodate different crack types.	In order to measure the size of defects, ACFM pencil probes need to lie between certain angles, while this drawback is overcome in ACFM arrays.
Electromagnetic acoustic transducers (EMATs)	They operate without the need for physical coupling or acoustic matching.	Cannot detect any defects smaller than 2 mm.
Ultrasonic phased arrays	Compared with conventional ultrasonic systems, the ultrasonic beam can be steered, scanned, swept and focused electronically.	Data processing is complicated.
Laser scanner	Accurately reconstructs spaces. Collects highly precise data for realistic drawings.	Data processing is complicated. The scanning file is relatively large.

2.4 Current rolling stock maintenance demands and future needs in the UK

In recent years, the number of passengers and amount of freight in the UK rail industry have grown at an unprecedented rate. However, expansion of network capacity and asset renewal have not kept pace with this growth. It has resulted in severe overcrowding and asset-ageing problems. The UK government, however, has recently set out a series of demands hoping to increase rail traffic. The Department for Transport has stated that it wants the railway [49]:

- To deal with a doubling of passenger and freight traffic;
- To be safer and more reliable and efficient;
- To cater for a more diverse, demanding and affluent population;
- To reduce its carbon footprint and improve its environment performance.

Of particular relevance to maintenance is the requirement to be safer and more reliable.

One of the important reasons for introducing RAS was the desire to improve the performance of maintenance system. The following literature in this section reviews and summarises some common performance indicators used in maintenance systems. Further system performance indicator selection and the methods of analysis of the individual indicators will be presented in Chapter 4.

European Standard BS EN 13306:2010 lists the following main maintenance strategy objectives [32]:

- To ensure the availability of the item to function as required, at optimum cost;
- To consider the safety and any other mandatory requirements associated with the item;
- To consider any impact on the environment;
- To uphold the durability of the item and/or the quality of the product or service provided, considering costs where necessary.

The European standard defines maintenance targets including availability, cost reduction, product quality, environment preservation and safety. Some scholars have also proposed that the measurement of reliability, availability, maintainability and safety (RAMS) can be the key performance indicators [50]. It can be summarised that the emphasis on railway maintenance is to improve the reliability, safety and availability with time and cost constraints.

Among all these factors, safety is paramount since neglecting minor errors may lead to disasters. For example, the Eschede derailment which occurred in Germany on 3 June 1998 involved Deutsche Bahn's Inter City Express (ICT) train, ICE 884. It derailed at a speed of approximately 250 km/h and crashed into a viaduct which then collapsed onto the train. The accident resulted in the death of 101 people, and more than 100 were injured. To date, it is the worst railway disaster in the history of the Federal Republic of Germany. The accident was caused by a fatigue crack which led to a wheel-tyre failure. The Eschede disaster illustrates that the realistic measurement of service loads is necessary, and that regular and reliable maintenance checks are crucial [51].

There are challenges in terms of adapting the increasing demands for conventional maintenance programmes. Therefore, there has been a high demand for railway maintenance innovation due to the shortcomings arising from conventional manual maintenance, such as hazardous working environments, the tediousness of repetitive tasks, high training costs and frequent occurrence of human errors [52][53].

Human error is defined as the failure to perform a specific task that could lead to disruption of a scheduled operation or result in damage to property and equipment [1]. The reasons for human errors include inadequate lighting in the working area, inadequate training or skills of the people involved, poor equipment design, high noise levels, inadequate work layout, improper tools, and poorly written equipment maintenance and operating procedures. Dhillon and Liu stated that it is nearly impossible to eradicate human error during human activities [53].

Safety is a critical issue not only in the railway industry but also in other business sectors. For instance, image-guided robotic systems have been used routinely in the medical industry to ensure precise joint replacements and to guide biopsy of brain lesions [54]. B. Fei et al. discussed the safety issues of medical robotics, and drew the conclusion that the chosen robotic system met the IEC 601 standard and is capable of significantly enhancing safety during surgery [55].

Safety is a fundamental issue for railway transport, and it is noteworthy that RAS has been an effective tool in minimising human errors. It shows great potential for the maintenance sector as a number of applications have already been developed for maintenance and inspection tasks. The following sections will investigate whether RAS would also be an appropriate solution to improve maintenance practices.

2.5 RAS applications in inspection and railway maintenance

Robotics is defined as a branch of engineering that focuses on the design, construction and operation of physical machines performing a range of particular tasks. Autonomous systems cover a wider range, and are defined as self-monitoring adaptive intelligent systems with a high degree of autonomy [13].

Transport was one of the earliest industries to get benefits from RAS. As early as 1987, Martland reviewed a few robots which had been installed in railway maintenance settings to get involved in activities including welding, grinding, cleaning and painting. These applications of robotics proved to be a great help for improving efficiency [56]. After that, use of RAS has also been extended to maintenance and inspection of infrastructure and rolling stock; examples are as follows [57].

An automatic track inspection trolley named FELIX was developed by Loccioni Research for Innovation and Rete Ferroviaria Italiana (RFI) in 2014, with the aim to improve inspection reliability and safety.

FELIX is the first certified robot approved by Bureau Veritas in Accredia Laboratories [54]. The robot automatically inspects switches and crossings as well as wearing components. It has the flexibility to perform different measurements and adapt to the different types of railway switches and crossings and is able to work in almost any environmental conditions. It is used to guarantee high metrological performance and eliminate human and clerical errors. FELIX complies with standard EN 13848 for measurement rules and EN 2859, EN 17025 and EN 13005 to ensure reliable and accurate operation. This case demonstrates that robotic systems have reached a higher technology readiness level (TRL) which has been operated in the relevant environment.

Figure 2.3 FELIX robot, Loccioni[54]

A wayside acoustic monitoring system developed by researchers from BCRRE is used for detecting and characterising faulty axle bearings [58], and an automatic laser-based inspection system is used in switches and crossings (Figure 2.5) [59]. Moreover, this automatic inspection system has been tested both on track samples in the laboratory and on the Long Marston Rail

Test Track. The testing results demonstrate the feasibility of applying automatic 3D reconstruction-based inspection to railway systems. Obtaining a 3D model of the surrounding objects is very important for RAS application, and 3D reconstruction techniques are widely applied in environment navigation and prediction [60]. The application of 3D reconstruction in railways demonstrates that RAS can deal with the complex railway environment.

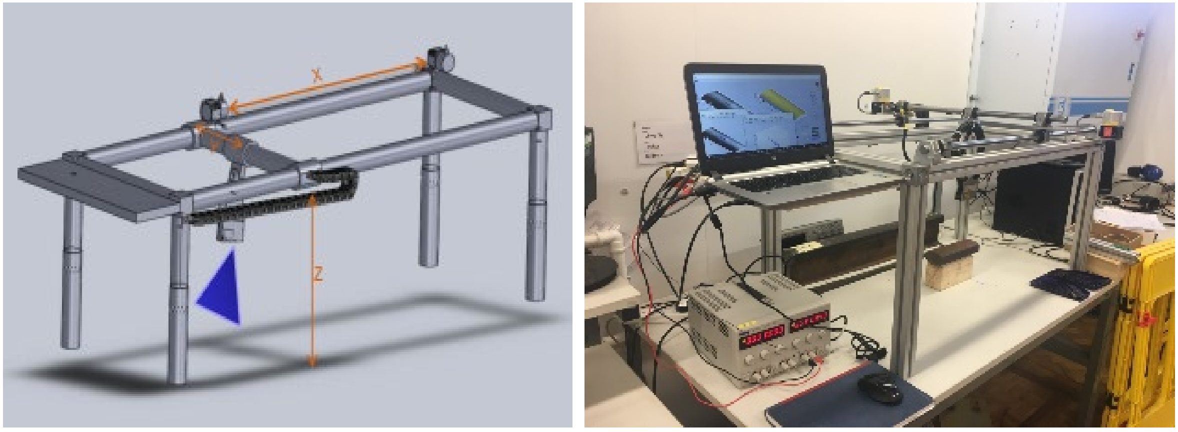


Figure 2.4 Laser-based inspection system at the University of Birmingham[59]

In the aerospace industry, a typical case is the IntACom project led by TWI's Advanced Non-destructive Testing Centre in Port Talbot, South Wales, which has established a prototype automatic NDI system for aerospace components inspection (Figure 2.6).

IntACom is an innovative development programme which aims to improve the inspection efficiency of complex geometric components. It has the following sub-objectives: (1) automate the current fully manual inspection process; (2) improve the levels of autonomation of existing semi-automated systems; (3) enhance the human–machine interface and console software through the use of technologies such as defect recognition and display management.

The ultimately developed inspection cell comprises of two 6-axis KUKA robotic arms which can operate independently and cooperatively. The end effectors of the robot currently carry Phased Array Ultrasonic Testing (PAUT) probes, while it is capable of deploying a variety of NDT tools depending on inspection objects. The console interface was designed as a fully integrated communication platform for data acquisition, transmit and processing. As a consequence, this system demonstrates the feasibility of fully automated NDI with the result of improved inspection throughout [61].

Figure 2.5 IntACom project developed by TWI Technology Centre (Wales) [61]

It can be summarised that RAS is technically feasible for railway track maintenance. However, the implementation of RAS is not easy, and there are always many non-technical prerequisites for further development. Especially given the fact that the railway is a highly regulated industry, the intention of using RAS would theoretically improve maintenance effectiveness, freeing technicians from monotonous and dangerous tasks and thus improving reliability. In the meantime, the impact of regulatory challenges, standard changes, test rig development, technically acceptable levels, the safety issues of RAS, and staff skill development are essential factors to overcome [30]. Hence, the function allocation problem needs to be widely considered, and will be discussed in Chapters 4 and 5.

2.6 Function allocation methods

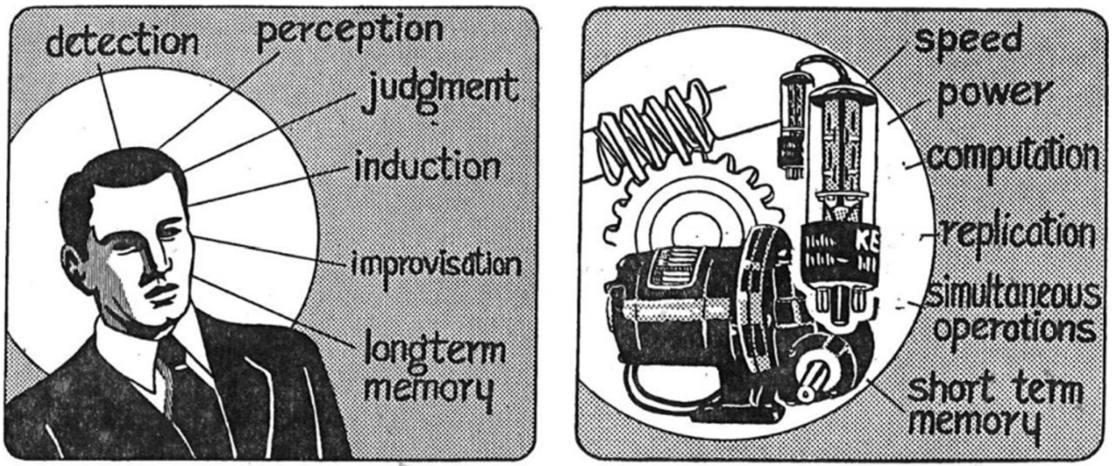
The argument of what tasks to automate and what should remain with human operators has never stopped since automation emerged. In brief, there are two options for automation design. One is trying to automate everything, leaving humans with functions which are really expensive or impossible to automate. Choice of this strategy is often made because a single issue (improve efficiency, ensure safety or tough for humans etc.) is the major motivation for achieving automation. For example, in a factory that involves large facilities and heavy manipulation, there is usually a high degree of automation [61]. The other option is to match human and machine capabilities; functions which machines do better would be automated, whereas functions which humans perform better would not [62]. This automation alternative applies to those complex systems with multiple issues which need to be traded off, such as in the railway industry. The methodologies of guiding how functions are assigned between humans and machine are reviewed below.

2.6.1 Fitts list

One of the first methodologies was proposed by Fitts et al. in 1951 [63]; their famous theory lists the capabilities and limitations of humans and machines to optimise the distribution of functions. The Fitts list put forward the concept of function allocation and pointed out that it is not important how to automate but the impact of automation. Since then, function allocation has stepped into science [24] and this classic theory has persisted throughout the history of function allocation [26].

In their report, the authors listed a series of capabilities in which either a machine or a human would perform better (Figure 2.7), also known by the acronym 'MABA-MABA' (men are better at/machines are better at). In the literal interpretation, humans and machines are regarded as separate system modules with different capabilities; only functions performed better by machines should be automated. In spite of criticisms of the Fitts list, such as it giving too general a description, and its limitations in fitting dynamic environments and practical engineering design, it has persisted throughout the history of function allocation [26].

The Fitts list is a famous mechanism to determine whether humans or machines would perform a certain function better, aiming to optimise the distribution of functions between the two. It has been applied to both cognitive and physical tasks, concerned with the fact that automation would change the nature of tasks. It also recognises the importance of human capabilities. These advantages would make it suitable in the preliminary stage of railway maintenance allocation.



- Ability to detect small amount of visual or acoustic energy.
- Ability to perceive patterns of light or sound.
- Ability to improvise and use flexible procedures.
- Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time.
- Ability to reason inductively.
- Ability to exercise judgment.

- Ability to respond quickly to control signals, and to apply great force smoothly and precisely.
- Ability to perform repetitive, routine tasks.
- Ability to store information briefly and then to erase it completely.
- Ability to reason deductively, including computational ability.
- Ability to reason handle highly complex operations, i.e., to do many different things at once.

Figure 2.6 Fitts list (1951) [63]

However, the aim of the Fitts list is to ‘search for a general answer to the problem of dividing responsibility between men and machines’; it is a useful principle, but has been proved to be difficult to apply in practice [62]. Fitts himself admitted that the list does not take into account either the working context nor the dynamic flow of information [64]. In 1985, Price argued that the Fitts list is overly general, nonquantitative and incompatible with engineering concepts, which gives it little impact on engineering design practice [65]. Dekker and Woods also argued that MABA-MABA cannot provide guidance on human–automation coordination [66]. Also, rather than a simple replacement of humans, use of machines is more about augmenting inherent human capabilities nowadays [67].

It should also be noted that with the development of technologies, machine performance has surpassed that of humans already in terms of some characteristics, such as detection and perception. Hence, some researchers have reviewed the Fitts list and concluded that machines have surpassed humans in some characteristics.

J. C. F. de Winter and P. A. Hancock analysed the original Fitts list and pointed out that at present, humans apparently consider that machines surpass humans in detection, perception and long-term memory[68]. The advancement in machine performance is evidently related to improvements in sensor technology, artificial intelligence and computer data storage capacity. As can be seen from the review in Section 2.5, some detection and perception activities have been automated in the railway industry, such as various automated sensing and inspection systems and the application of intelligent fault diagnosis and fault feature extraction algorithms [69][70]. For the aspect of long-term memory, the railway industry already uses a wide range of disaggregated databases for storing, managing and analysing information. For example, Network Rail has an intelligent database to record daily asset fault information. This information can be traced back up to 5 years or more, which is not possible with humans. In summary, the author agrees with de Winter and Hancock that machines in the rail industry also outperform humans in detection, perception and long-term memory.

Therefore, the updated Fitts list is shown in Table 2-2, which will be applied in Chapters 5 and 6.

Table 2-2 Updated Fitts List [69]

Humans are better at	**Machines are better at**
Ability to improvise and use flexible procedures.	Ability to detect small amounts of visual or acoustic energy. (Updated)
Ability to reason inductively.	Ability to perceive patterns of light or sound. (Updated)
Ability to exercise judgement.	Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time. (Updated)
	Ability to respond quickly to control signals, and to apply great force smoothly and precisely.
	Ability to perform repetitive, routine tasks.
	Ability to store information briefly and then to erase it completely.
	Ability to reason deductively, including computational ability.
	Ability to reason while handling highly complex operations, i.e., to do many different things at once.

2.6.2 Levels of automation

Following on from Fitts's theory, researchers have come to realise that in most cases a function is not completely manual or fully automated, but more often by the collaboration of humans and machines[71]. In railway maintenance systems, there are many tasks that require both humans and machines get involved. To help understand and define how humans interact with automation, levels of automation (LOAs) was reviewed.

LOAs have been investigated by many researchers from different areas such as the aviation and telerobotic industries [62][72][73]. Based on the review, it can be argued that automation is not only a matter of 'all or nothing', but also involves a decision on the extent of automation. The LOA concept implies that automation levels vary over a continuum, from fully manual through partially automated to fully automated.

The first theory is a 10-scale taxonomy proposed by Sheridan and Verplank [71], which is focused on human–computer interaction in the context of teleoperation systems (Table 2-3). For example, at level 2, the computer provides decision/action alternatives but cannot get involved in decision-making. Instead, at the high level 9, the computer decides almost every action and only gives humans a notice when needed.

Table 2-3 LOAs for decision and action selection[71]

Level	Description
1	The computer offers no assistance; the human must make all decisions and actions
2	The computer offers a complete set of decision/action alternatives, or
3	Narrows the selection down to a few, or
4	Suggests one alternative
5	Executes that suggestion if the human operator approves, or
6	Allows the human a restricted time to veto before automatic execution, or
7	Executes automatically, then necessarily informs the human, and
8	Informs the human only if asked, or
9	Informs the human only if it, the computer, decides to
10	The computer decides everything, acting autonomously, ignoring the human

However, some scholars argue that the 10-level categorisation scheme is too redundant and restrictive. It is not applicable for many other industries such as production [74]. Depending on different applications, there are many other classification taxonomies. For example, in railway practices, the Rail Safety and Standards Board (RSSB) has chosen the six-level version proposed by the US Navy Office (Table 2-4)[52]. This six-level version is widely used in transportation; it implies that LOAs are associated with the degree of human intervention or interaction activities and there is no clear boundary between each level.

Table 2-4 US Navy Office of Naval Research LOAs, used by SEAS DTC [53]

1	Human-operated	All activity within the system is the direct result of human-initiated control inputs. The system has no autonomous control of its environment, although it may have information-only responses to sensed data.
2	Human-assisted	The system can perform activity in parallel with human input, acting to augment the ability of the human to perform the desired activity, but has no ability to act without accompanying human input. An example is automobile automatic transmission and antiskid brakes.
3	Human-delegated	The system can perform limited control activity on a delegated basis. This level encompasses automatic flight controls, engine controls and other low-level automation that must be activated or deactivated by a human input and acts in mutual exclusion with human operation.
4	Human-supervised	The system can perform a wide variety of activities given top-level permissions or direction by a human. The system provides sufficient insight into its internal operations and behaviours that it can be understood by its human supervisor and appropriately redirected. The system does not have the capability to self-initiate behaviours that are not within the scope of its current directed tasks.
5	Mixed initiative	Both the human and the system can initiate behaviours based on sensed data. The system can coordinate its behaviour with the human's behaviours both explicitly and implicitly. The human can understand the behaviours of the system in the same way that they understand their own behaviours. A variety of means are provided to regulate the authority of the system with respect to human operators.
6	Fully autonomous	The system requires no human intervention to perform any of its designed activities across all planned ranges of environmental conditions.

The LOAs are aimed at one single function of a system. For example, Table 2-3 mainly discusses the automation of decision selection within a teleoperation system. However, automation may be applied to the entire system. In the expansion of LOAs, Parasuraman, Sheridan and Wickens [62] adopted a simple four-stage view of human information processing on the basis of LOA theory. A revised taxonomy model was proposed by associating the LOAs to four different categories of functions:

- Information acquisition

  It involves sensing and information registration from various sources.

- Information analysis

  It includes retrieved data from memories and processing information into cognitive operations or manipulation commands.

- Decision action and action selection

  It refers to operation selection based on the alternatives retrieved from the previous step.

- Action implementation

  It is the implementation or response to the decision choice.

The theory suggests that automation is applied to different types of system functions (acquisition, analysis, decision and action); LOAs are decided separately [62].

An example of railway inspection system analysis is presented in Figure 2.8. It combines the four-stage model and US Navy six-scale LOAs. The cognitive processes of railway inspection are considered from four aspects (acquisition, analysis, decision and action) and each aspect is divided into six-scale LOAs. Figure 2.8 implies the following information:

- A six-scale LOA is selected;
- Both information acquisition and information analysis are at the relatively high level 4, which implies that RAS can understand and perform a wide variety of activities with

human guidance. However, it has limited capability for self-initiated actions. For example, data acquisition actions may trigger according to some commands or criteria. Data analysis at level 4 may involve a data integration platform for data filtering and processing and storage;

- The third stage is decision selection among alternatives. Different LOAs vary from operation and argumentation to thoroughly overthrowing the human's decision. Level 2 in this figure indicates that the system can work together with humans to enhance decision-making;
- A fully automated action implementation means the system is executive and acts autonomously.

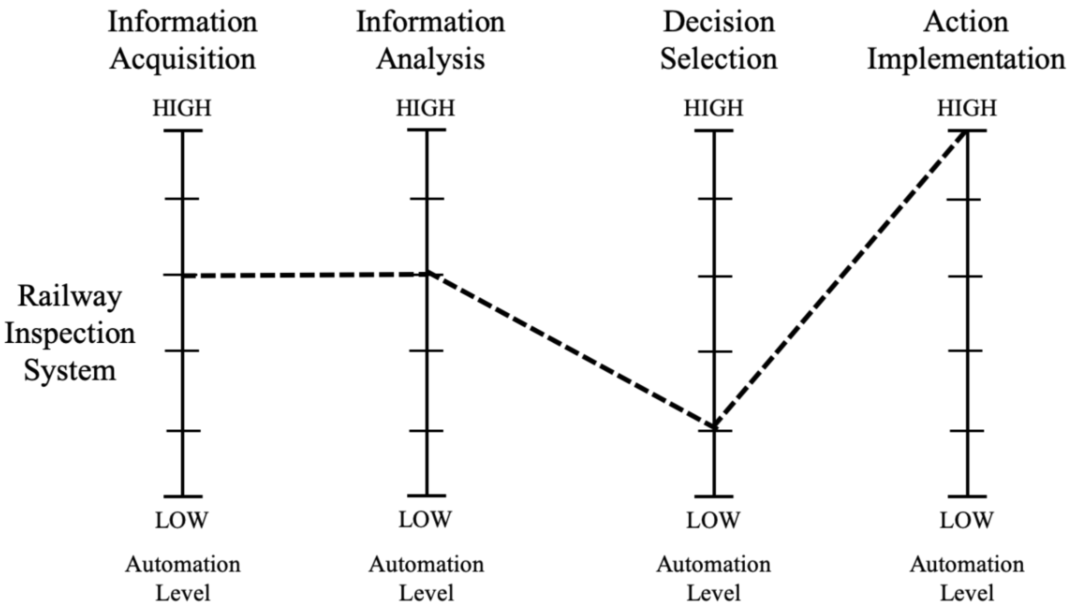


Figure 2.7 LOAs of a railway inspection system

LOA theories propose that humans and machines are cooperative rather than antagonistic. While some scholars have noted that most LOA literature considers the various LOAs equivalent to the stages of human cognitive processing, few publications have discussed the automation of manipulation tasks. Williams and Li [75] pointed out that automation should consider both mechanisation and computerisation tasks. Frohm and Bellgran [76] also observed that most tasks in manufacturing are a mix of both mechanisation and computerisation, and therefore suggested that LOAs in a manufacturing context need to be assessed physically and cognitively respectively. In terms of mechanisation, LOAs can be either manual, semi-automatic or automatic, as shown in Table 2-5.

Table 2-5 Three levels of mechanisation [77]

Mechanisation LOAs	Description
1. Manual Assembly	Tasks are achieved without any support of automation
2. Semi-automatic equipment	E.g. automated alignment, automatic process, automatic cassettes
3. Automatic	E.g. Robotic material handling, automated inter-cell transfer

Similarly, Groover also said that the 'level of mechanisation' can be defined as manual, semi-automatic or fully automatic [77]. Railway maintenance involves both cognitive and manipulation tasks; LOAs need to be considered from there two aspects as well.

2.6.3 Function allocation model examples

Based on the foundation of the Fitts list and LOAs, researchers have proposed some more sophisticated models to meet different automation requirements.

From the point of view of how a machine could replicate human behaviour, Rasmussen proposed a behavioural trinity that comes to dominate everyday task execution (Figure 2.9) [78].

- Skill-based behaviour
- Rule-based behaviour
- Knowledge-based behaviour

The model describes human performance from the information cognitive aspect to physical actions and covers a wide range, from daily routine tasks to accidental events. The aim of this model is to distinguish categories of human performance and their interrelation, ultimately aiding the optimal design of a human–machine interface. Different types of models that represent performance based on skills, rules, and knowledge levels are considered, together with a review of different methods about information preservation at different levels in terms of signals, signs and symbols.

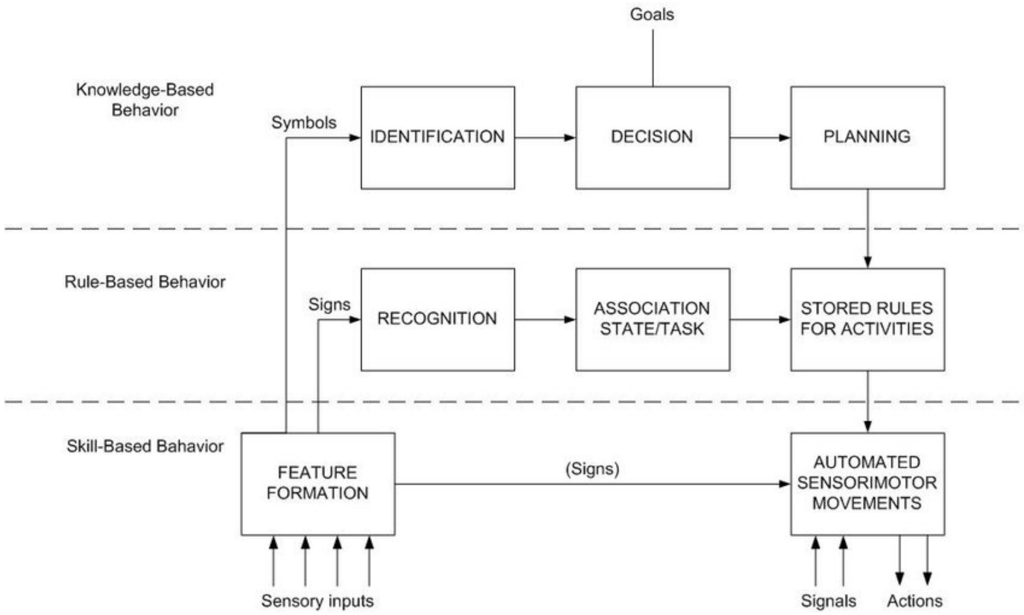


Figure 2.8 Knowledge-, rule- and skill-based human performance model[78]

In terms of system performance, Price revealed a logical error that few allocation methods assume that if a machine is a bad controller, then the human must be a good one and vice versa (Figure 2.10) [79]. In reality, however, neither humans nor machines can properly handle certain tasks. In some cases, there are tasks that both can perform very well [65]. Starting with this new concept, a novel model was proposed.

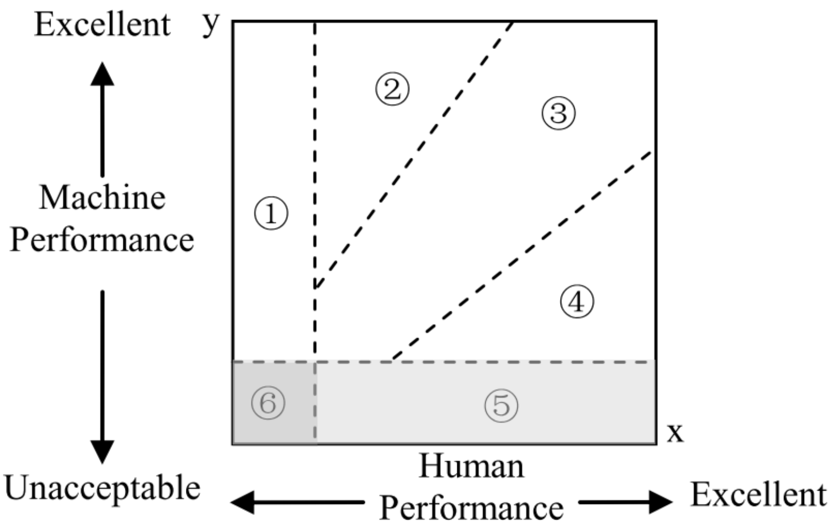


Figure 2.9 Decision-making matrix [79]**, The six regions are described in Table 2-6**

Price's decision matrix represents a decision space where the x-axis is the judgment variable of human performance, from unacceptable to excellent, and the y-axis is the corresponding variable of machine performance. Any function can be represented by a point in the decision space. Price's decision matrix consists of six regions that imply performance-based allocation, as shown in Table 2-6.

Table 2-6 Illustration of Price's matrix [80]

Region	Corresponding function allocation suggestions
1	Functions are performed poorly by humans and at least acceptably by machines. Suggestion: allocate to machine.
2	Functions can be allocated either to machines or to humans, while machines are slightly better. Suggestion: allocate to machines, if there is no strong reason not to do so.
3	There is a minor difference between humans and machines in terms of performance. Suggestion: other criteria are required to aid function allocation.
4	Functions can be allocated either to machines or to humans, while humans are slightly better. Suggestion: allocate to humans, if there is no strong reason not to do so.
5	Functions are performed poorly by machines and at least acceptably by humans. Suggestion: allocate to humans.
6	Functions are performed unacceptably by both humans and machines. Suggestion: The system should be redesigned to avoid this function.

However, Price explains neither the performance indicators nor the evaluation process. The description of the allocation decision process for the six regions is also vague. Therefore, this method is difficult to use in practice.

Then, to find out the evaluation process, Parasuraman et al. suggested that after applying the primary criteria, LOAs could be re-evaluated with respect to a few sub-criteria if needed, in an iterative manner, until generating an unambiguous allocation result. This model provides the idea that all important issues relevant to the function allocation should be profitably explored.

However, the authors themselves stated that their model only provides a simple guide rather than a comprehensive principle. Furthermore, the model assumes the operating environment is constant and predictable. It also expects that automation features to be selected during the initial iteration phase are appropriate for the entire evaluation process [80].

These three models above illustrate that differences in focus can lead to completely different allocation strategies, for example in terms of behavioural approaches, in terms of the system performance as a whole, or in terms of processes.

As stated in Section 1.2, railway maintenance systems are complex, composed of many sub-systems that interact with each other; automation is always associated with human factors and the allocation has direct effects on the operating mechanism of systems. It can be argued that the function allocation for railway maintenance encompasses all factors of human behaviour, system processes and system performance, and even others such as different stakeholders. The existing methods are not applicable.

2.7 The need for novel function allocation in railway maintenance

A comprehensive review of the function allocation theories is given in this chapter. Based on the review, it can be summarised that the difficulty of using these methods in practice is that the models are generally inexhaustive. Furthermore, current methods are all designed for specific systems such as aerospace and human–computer control interfaces, which might result in limited applicability in railway maintenance.

A novel function allocation framework is necessary to meet the demands in the railway context. Based on existing function allocation literature, the following chapters will provide insights into maintenance systems and aim to propose a novel function allocation method.

CHAPTER 3 THE DECISION-MAKING PROCESS FOR COMPLEX SYSTEMS

As discussed in Section 1.3 and Chapter 2, railway system function allocation is a complex problem in which various factors need to be wisely considered. Systems engineering (SE) is an interdisciplinary approach, concerned with large and complex systems. It is dedicated to ensuring the successful delivery of a project in terms of performance, budgets, timelines and ongoing maintenance [81]. Research indicates that effective use of SE can save 10–20% of the project budget [17]. SE has a wide range of applications in railway systems and associated projects. J. Wilson et al. applied SE tools for railway human factor research [82]. Another example based on the SE model is the Governance for Railway Investment Projects (GRIP) published by Network Rail, which provides guidance on the investment process through the life cycle [83]. It includes eight stages, from output definition, project feasibility and option selection to the final project close-out to manage and control railway investment projects.

According to F. Schmid and R. Evans [17], SE copes with complexity, managing real-world change issues, considering the whole problem, the whole system and the whole life cycle from concept to disposal. It reduces the risk of project failure and ultimately aims to produce efficient, economic and robust solutions to build the right system. As these characteristics correspond inherently to the function allocation challenges summarised in Chapter 1.2, SE was chosen as the main approach used in this study to cope with complexity.

This chapter starts with an introduction to the decision-making methods commonly used in SE. Then, the multi-criteria decision-making (MCDM) concept is discussed with a practical example.

3.1 Decision-making in SE projects

SE naturally considers the system as a whole and makes reasoned decisions about how the internal elements of the system should interact with each other [84]. To achieve this, standard frameworks are often used in SE to formalise the process of evaluating the interactions between sub-systems. Formalised processes cover aspects from conceptual, preliminary and detailed design to system testing, evaluation and validation.

Decision-making is one of the most important formalised processes used to choose alternatives based on predefined criteria or the preference of decision makers as part of SE theory. Applying SE technique in most cases involves the application of formal decision-making processes [18]. In general, decision-making is considered as a problem-solving process leading to the selection of a satisfactory solution [85]. A clear, formal and disciplined decision-making method helps to avoid doubts about the validity of results. According to Baker et al. [86], a generic decision-making process includes the following eight steps (Figure 3.1):

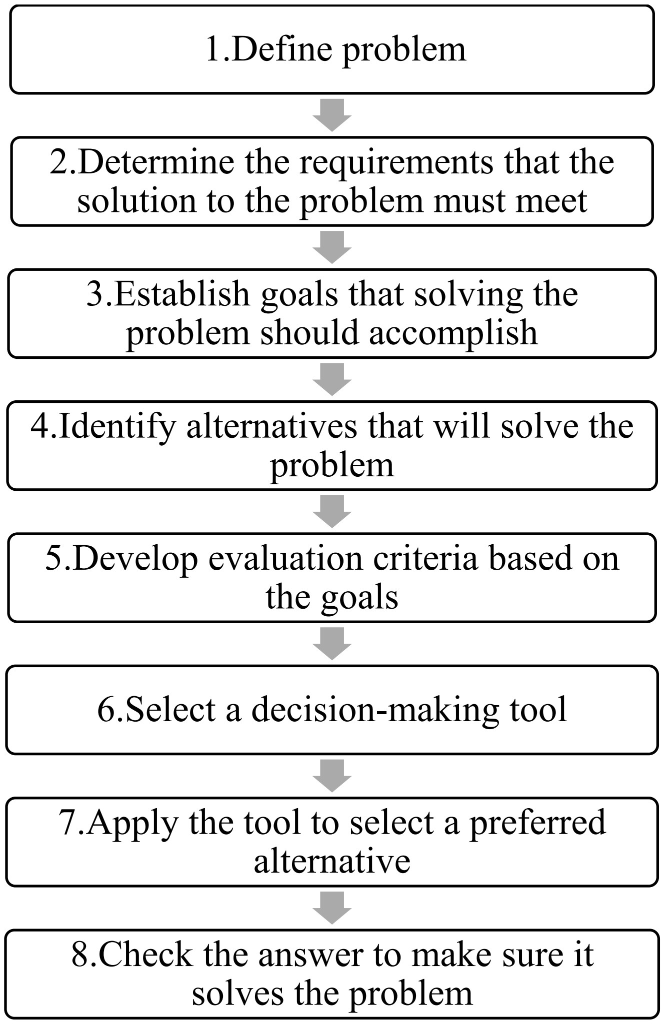


Figure 3.1 Generic decision-making process [86]

As illustrated in steps 1 to 4, a decision-making process typically starts by defining a problem and proposing a clear problem statement, followed by identifying the conditions that the final solution must meet. Then the aims and objectives should be discussed, and it is also necessary to suggest alternatives that meet the requirements.

In step 5, a decision-making problem needs to make a distinction between the cases whether single or multiple criteria are presented. If there are a finite number of alternatives subject to several evaluation criteria, then it can be defined as an MCDM problem. Otherwise, it may have a single criterion, and the final decision can be made implicitly by determining the optimal value [87].

Depending on the complexity, steps 6 and 7 may appear in the following two phases of analysis [86]:

Phase I – Qualitative Analysis

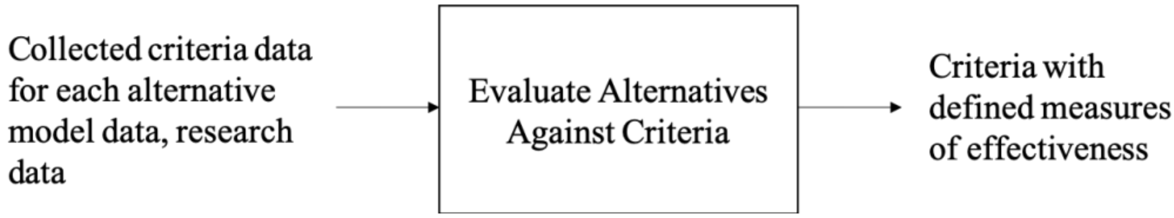


Figure 3.2 Qualitative analysis [86]

Qualitative analysis was initially employed in social research to delve into human behaviours. The qualitative method provides a deep understanding of the problem's complexity. It normally intends to investigate the experiences and attitudes of participants. Typical data collection methods include participant observation, in-depth interviews and questionnaires to produce descriptive data [88]. The process is not only time-consuming and expensive but also much more influenced by the personality of the researcher than in quantitative research[89].

Phase II – Quantitative Analysis

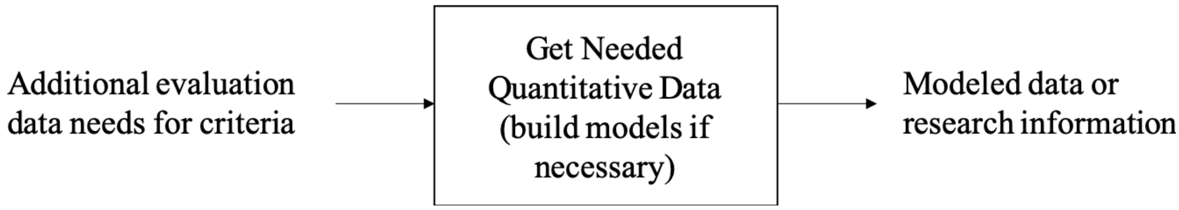


Figure 3.3 Quantitative analysis[86]

Alternatively, standard quantitative analysis emphases a statistical approach and deductive results. K. McCusker and S. Gunaydin [89] suggested that quantitative methods help to separate researchers from emotional and subjective bias. Thus, they enable a relatively objective hypothesis for validation. In social-technical system analysis, a quantitative approach is preferred from the viewpoint of efficiency and finance. However, Bryman [90] argues that quantitative methods have little concern about the impact of resource constraints. Eldabi et al. [91] pointed out that quantitative analysis is unable to reflect the variance between human beings and natural sciences, and applying it to the study of humans is questioned. Many researchers therefore focus on a mixed method using both quantitative and/or qualitative approaches in terms of data collection and analysis in a single study [92],[93]. A mixed solution takes the advantages of both methods and provides a more flexible solution for the decision maker. It is worth noting that MCDM is a decision-making technique containing both qualitative and quantitative factors [94].

The final step in Figure 3.1is validating the solution to ensure it truly solves the problem.

This study focuses on determining the type of functions to be allocated to humans and machines. Such allocation needs to consider a number of factors and may consist of both qualitative and quantitative analysis, such as human and machine capabilities, ergonomics, system efficiency and costs associated with different LOAs. Hence, application of MCDM is considered to be more appropriate.

3.2 MCDM and cost–benefit analysis (CBA)

The MCDM approach is the most well-known branch of decision-making processes [94] and one of the SE decision-making models which aims to find the optimal choice for a problem which has more than one evaluation criterion [95]. It is suitable for solving problems with high uncertainty, conflicting goals, different forms of data/information, and complex issues of socio-economic systems [96]. The MCDM method is also one of the most widely applied decision-making methodologies in various fields such as railways [97],[98], energy [99], economic systems [100] and aerospace [79]. It is a rational and explicit method that effectively improves decision quality [94]. Figure 3.4 presents the general structure of the MCDM process [101].

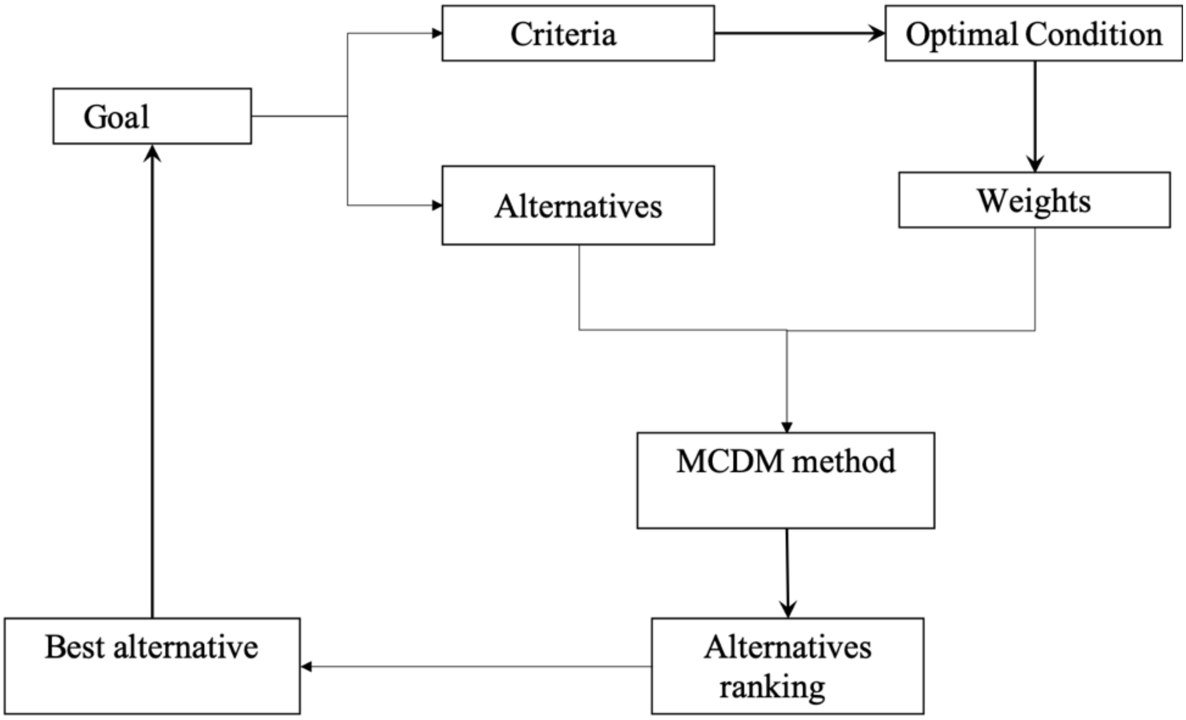


Figure 3.4 General structure of the MCDM process[101]

As shown in Figure 3.4, starting from the goal definition, the first step is to precisely define relative criteria and alternatives. With applied MCDM techniques and weighting methods, alternatives are then assessed referring to each criterion. The alternative ranking is then derived, and the decision maker chooses the option with the highest ranking as the best alternative.

The key steps of an MCDM process involve: defining the problem, determining evaluation criteria and alternatives, the weighting methodology, ranking alternatives and final decision-making [102].

As discussed, SE projects need to satisfy multiple stakeholders' requirements and multiple criteria. The matrix format is used extensively to represent an MCDM problem [103]:

$$\begin{bmatrix} st_1 \\ st_2 \\ \vdots \\ st_m \end{bmatrix} ? \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix} = \begin{bmatrix} w_1 & w_2 & \cdots & w_n \end{bmatrix} \tag{3.1}$$

Equation (1) represents the mathematical model of MCDM weighting. Element refers to the ith stakeholder, and element indicates the weighting of the ith stakeholder corresponding to the jth criterion. The element w_j denotes the final weighting of the ith criterion. The symbol '?' represents different operations when using different MCDM tools.

The method of deriving weighting values and ranking alternatives may different in different MCDM tools. The most commonly used methods applied in SE projects are the analytic hierarchy process (AHP), goal programming and Elimination and Choice Expressing and Reality (ELECTRE) [103]. According to the review of G. Kabir et al. [104], AHP is the most popular technique in the transportation industry.

T. L. Saaty[105] proposed AHP as an approach for numerical measurement through pairwise comparisons and relying on expert judgment to derive alternative priorities. It is applicable for both qualitative and quantitative information. AHP is decomposed using the following four steps [106]:

1. Define the decision-making problem and the type of knowledge sought.
2. Decompose the problem into several top-down hierarchies. The top includes the goal of the decision, the objectives from different perspectives; the intermediate layer is criteria; and the lowest level is the alternatives.
3. Construct a series of pairwise comparisons between each alternative against each criterion and transfer to a set of comparison matrices.
4. Transfer the weights obtained from comparisons to a matrix then calculate the principal right eigenvector.

AHP is easy to apply and flexible to use, and it can also incorporate a broad perspective of views via judgments by different stakeholders [105]. It is a classical theory for building a function allocation model [79], and has been applied for intelligent fire and command control systems [107], cockpit fault diagnosis systems [108] and air traffic control systems [109].

Furthermore, AHP is also used to allocate tasks to team players based on their skills, experience and workload [110].

However, one limitation of AHP is that pairwise comparison computations are complex and time-consuming; therefore, it is not appropriate for problems with a large number of alternatives.

Instead, goal programming is able to aid decision-making from an infinite number of alternatives for handling large scale problems. It has seen applications in economics and computer science for designing, planning, scheduling and selection problems. A major disadvantage of this method is the inability to provide criteria weight coefficients [111]. Many applications of goal programming use other MCDM methods complementarily to provide weighting.

ELECTRE is an outranking method consisting of many iterative processes where uncertainty and vagueness are eliminated by iteration. The main limitation of ELECTRE is that all criteria proceed as qualitative factors [112]. Furthermore, the evaluation process is hard to explain and the outcome may not include confidence factors [103].

Cost is one of the most noteworthy aspects in the system planning phase and is always considered separately. T. Besley et al. [113] indicate that investment is at the heart of innovation and resource relocation, and a supportive investment environment is paramount for the process of automation. It is thus important to recognise that maintenance performance and economics must be treated together in order to perform an objective CBA. Apart from MCDM, CBA is another crucial decision-making tool, especially in the early phase evaluation of a project [114],[115]. CBA is a technique which is used to appraise economic efficiency through prediction and valuation/monetisation analysis. CBA considers the costs incurred by and the benefits accruing to all system stakeholders [116].

In transport systems, the cost is the sum of the economic resources required to meet the project's expected outcomes. The costs of a project include the initial investment, the labour cost, the materials required for ongoing operation and maintenance, and the abandonment costs. In transport systems, these costs are usually estimated covering the whole project's lifetime, also known as life cycle costs (LCC). The benefit is defined as the economic value of positive outcomes that are reasonably expected from the implementation of a project. For example, passengers get benefit from the changes in the characteristics of the journey (e.g., reduced travel time). For society at large, benefits include reductions in carbon emissions, improved transport safety and reliability. In CBA, benefits are monetised throughout the analysis period, constituting the cost–benefit ratio, or calculation of net benefits [117]. After identifying associated cost and benefit values, depending on different scenarios, the following steps may include financial analysis, economic analysis, risk assessment or another evaluation approach, e.g., economic impact analysis and cost-effectiveness analysis [115]. Normally, CBA and MCDM are considered together in transport projects [118]; an application will be presented in Chapter 6. To demonstrate the MCDM process, AHP is selected as a typical example of MCDM, and a real-life example of the AHP method is provided in section 3.3.

3.3 AHP example

A real industrial scenario can help to clearly demonstrate how AHP could help to solve a problem with multiple criteria, and the process of how AHP could bring all criteria together, weight each criterion, and derive the final decision.

3.3.1 Defining the decision problem

One problem encountered is that vegetation may obscure the camera in a train station which may cause train delays. Engineers plan to do site inspections on those sites which previously had vegetation issues, thereby preventing failures before they affect services. Due to time and funding constraints, it is unrealistic to visit every station. One decision-making problem could be deciding which sites have the highest priority to visit.

According to the Fault Management System (FMS) record of Network Rail, the top five worst stations for camera performance in London in 2020 were Lewisham Station, Ladywell Station, Albany Park Station, Eden Park Station and Blackheath Station. Assuming engineers can only choose three to visit first, they may consider issues including a station's level of critical services, the number of faults reported, travel expenses and the time costs (assuming a start from London Waterloo Station). This example can be seen as an AHP with the goal of selecting the sites to visit.

3.3.2 Design of criteria, alternatives and construction of the hierarchy contracture

The example given in section 3.3.1 may be described by the hierarchy constructed as shown in Figure 3.5.

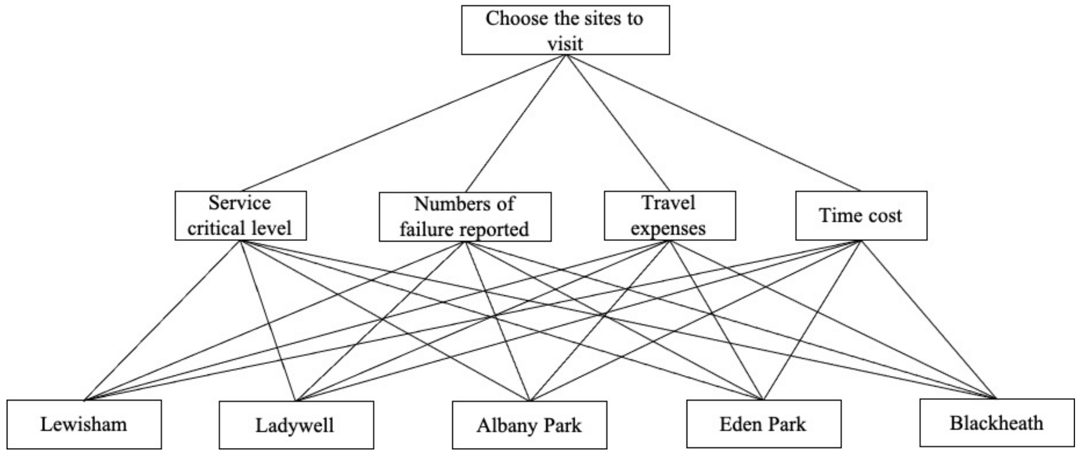


Figure 3.5 AHP example: decide which station to visit

3.3.3 Calculate pairwise comparison matrices

After building the hierarchy, the next step is to make the pairwise comparison and to judge the relative importance of each criterion with respect to the goal. Criteria need to be compared against each other to determine their relative significance. Information collection was done by a survey among the Asset Engineers. Table 3-1 demonstrates an example of such a survey, with the level of importance and intensity to be decided by decision makers. lists five scales of intensity from this assessment. For example, in the first line of Table 3-2, if the asset engineer believes compared with travel expenses, service critical level is more important and with an intensity of 9, it indicates that service critical level is extremely important compared with travel expenses. Table 3-3 presents sample comparison results based on the survey results.

Table 3-1 Pairwise comparison

Criterion 1	Criterion 2	Which criterion is more important?	Intensity
Service critical level	Numbers of failure reported		
Service critical level	Travel expenses		
Service critical level	Time cost		
Numbers of failure reported	Travel expenses		
Numbers of failure reported	Time cost		
Travel expenses	Time cost		

Table 3-2 Scale for quantitative comparison of criteria

Option	Numerical value
Equal	1
Marginally strong	3
Strong	5
Very strong	7
Extremely strong	9

Table 3-3 Comparison results

Criterion 1	Criterion 2	Which criterion is more important?	Intensity
Service critical level	Numbers of failure reported	Service critical level	3
Service critical level	Travel expenses	Service critical level	9
Service critical level	Time cost	Service critical level	7
Numbers of failure reported	Travel expenses	Numbers of failure reported	7
Numbers of failure reported	Time cost	Numbers of failure reported	5

Travel expenses	Time cost	Time cost	3

The pairwise comparison results are expressed in Table 3-4, in which comparison is made by the relative importance level.

Table 3-4 Relative importance level

Criteria	Service critical level	Numbers of failure reported	Travel expenses	Time cost
Service critical level	1.000	3.000	9.000	7.000
Numbers of failure reported	0.333	1.000	7.000	5.000
Travel expenses	0.111	0.143	1.000	0.333
Time cost	0.143	0.200	3.000	1.000

The numerical results of the importance can be converted to a matrix, as shown in Equation 2.

$$A = \begin{matrix} 1.000 & 3.000 & 9.000 & 7.000 \\ 0.333 & 1.000 & 7.000 & 5.000 \\ 0.111 & 0.143 & 1.000 & 0.333 \\ 0.143 & 0.200 & 3.000 & 1.000 \end{matrix} \tag{3.2}$$

At this point, the eigenvector of matrix A can be derived, representing the relative ranking of criteria (Equation 3.3):

$$Eigenvector = \begin{bmatrix} 0.886 \\ 0.440 \\ 0.064 \\ 0.129 \end{bmatrix} \tag{3.3}$$

$$\text{Standardized as} \begin{bmatrix} 0.583 \\ 0.290 \\ 0.042 \\ 0.085 \end{bmatrix} \tag{3.4}$$

The eigenvector indicates the priorities of each criterion shown in Table 3-4. Based on the eigenvalues, the hierarchy structure is updated as shown in Figure 3.6.

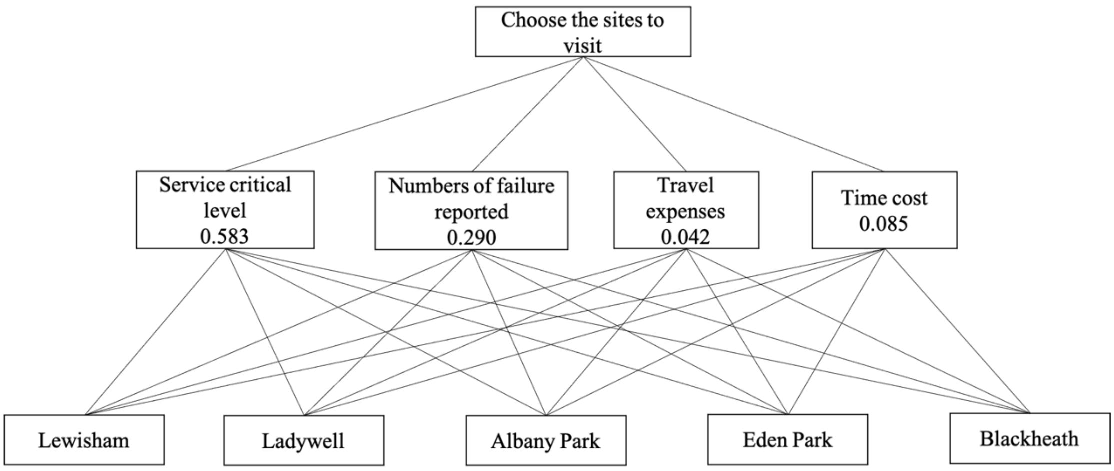


Figure 3.6 Updated AHP with criterion priority values

From the analysis above, it can be concluded that service-critical level and the number of failures are the major considerations for the decision maker. On the other hand, time costs and travel expenses have a relatively smaller impact on decision-making.

The next step is to evaluate alternatives for a single criterion and to list the priorities individually, as shown in Table 3-5 . For example, assume that the number of failures reported for the five stations in one period is 9, 5, 5, 5 and 4 for Lewisham, Ladywell, Albany Park, Eden Park and Blackheath, respectively. Then, the relative priorities can be derived as

$$Lewisham = \frac{9}{9+5+5+5+4} = 0.321. \quad (3.5)$$

$$Ladywell = \frac{5}{9+5+5+5+4} = 0.179 \quad (3.6)$$

$$Albany\ Park = \frac{5}{9+5+5+5+4} = 0.179. \quad (3.7)$$

$$Eden\ Park = \frac{5}{9+5+5+5+4} = 0.179. \quad (3.8)$$

$$Blackheath = \frac{4}{9+5+5+5+4} = 0.142. \quad (3.9)$$

Table 3-5 Alternative priorities

Alternatives	Priority based on **service critical level**
Lewisham	0.286
Ladywell	0.214
Albany Park	0.143
Eden Park	0.143
Blackheath	0.214
Total	1.000
Alternatives	Priority based on **numbers of failure reported**
Lewisham	0.321
Ladywell	0.179

Albany Park	0.179
Eden Park	0.179
Blackheath	0.142
Total	1.000
Alternatives	Priority based on travel expenses
Lewisham	0.214
Ladywell	0.214
Albany Park	0.183
Eden Park	0.183
Blackheath	0.204
Total	1.000
Alternatives	Priority based on **time cost**
Lewisham	0.216
Ladywell	0.216
Albany Park	0.181
Eden Park	0.181
Blackheath	0.207
Total	1.000

Table 3-5 can be converted into the pairwise comparison form (Table 3-6).

Table 3-6 Pairwise comparison form

Service critical level	Lewisham	Ladywell	Albany Park	Eden Park	Blackheath
Lewisham	1.000	1.336	2.000	2.000	1.336
Ladywell	0.748	1.000	1.497	1.497	1.000
Albany Park	0.500	0.668	1.000	1.000	0.668
Eden Park	0.500	0.668	1.000	1.000	0.668
Blackheath	0.748	1.000	1.497	1.497	1.000
Numbers of failure reported	Lewisham	Ladywell	Albany Park	Eden Park	Blackheath
Lewisham	1.000	1.793	1.793	1.793	2.261
Ladywell	0.558	1.000	1.000	1.000	1.261
Albany Park	0.558	1.000	1.000	1.000	1.261
Eden Park	0.558	1.000	1.000	1.000	1.261
Blackheath	0.442	0.793	0.793	0.793	1.000
Travel expenses	Lewisham	Ladywell	Albany Park	Eden Park	Blackheath
Lewisham	1.000	1.000	1.169	1.169	1.049
Ladywell	1.000	1.000	1.169	1.169	1.049
Albany Park	0.855	0.855	1.000	1.000	0.897
Eden Park	0.855	0.855	1.000	1.000	0.897
Blackheath	0.953	0.953	1.115	1.115	1.000

Time cost	Lewisham	Ladywell	Albany Park	Eden Park	Blackheath
Lewisham	1.000	1.000	1.193	1.193	1.043
Ladywell	1.000	1.000	1.193	1.193	1.043
Albany Park	0.838	0.838	1.000	1.000	0.874
Eden Park	0.838	0.838	1.000	1.000	0.874
Blackheath	0.958	0.958	1.144	1.144	1.000

Then, from Table 3-6, four matrices can be derived. Again, eigenvectors can be computed separately for the four criterion matrices as shown in Equations 3.10–3.17.

Service critical level

$$C_1 = \begin{bmatrix} 1.000 & 1.336 & 2.000 & 2.000 & 1.336 \\ 0.748 & 1.000 & 1.497 & 1.497 & 1.000 \\ 0.500 & 0.668 & 1.000 & 1.000 & 0.668 \\ 0.500 & 0.668 & 1.000 & 1.000 & 0.668 \\ 0.748 & 1.000 & 1.497 & 1.497 & 1.000 \end{bmatrix} \tag{3.10}$$

$$Eigenvector = \begin{bmatrix} 0.286 \\ 0.214 \\ 0.143 \\ 0.143 \\ 0.214 \end{bmatrix} \tag{3.11}$$

Numbers of failure reported

$$C_2 = \begin{bmatrix} 1.000 & 1.793 & 1.793 & 1.793 & 2.261 \\ 0.558 & 1.000 & 1.000 & 1.000 & 1.261 \\ 0.558 & 1.000 & 1.000 & 1.000 & 1.261 \\ 0.558 & 1.000 & 1.000 & 1.000 & 1.261 \\ 0.442 & 0.793 & 0.793 & 0.793 & 1.000 \end{bmatrix} \tag{3.12}$$

$$Eigenvector = \begin{bmatrix} 0.321 \\ 0.179 \\ 0.179 \\ 0.179 \\ 0.142 \end{bmatrix} \quad (3.13)$$

Travel expenses

$$C_3 = \begin{bmatrix} 1.000 & 1.000 & 1.169 & 1.169 & 1.049 \\ 1.000 & 1.000 & 1.169 & 1.169 & 1.049 \\ 0.855 & 0.855 & 1.000 & 1.000 & 0.897 \\ 0.855 & 0.855 & 1.000 & 1.000 & 0.897 \\ 0.953 & 0.953 & 1.115 & 1.115 & 1.000 \end{bmatrix} \quad (3.14)$$

$$Eigenvector = \begin{bmatrix} 0.214 \\ 0.214 \\ 0.183 \\ 0.183 \\ 0.203 \end{bmatrix} \quad (3.15)$$

Time cost

$$C_4 = \begin{bmatrix} 1.000 & 1.000 & 1.193 & 1.193 & 1.043 \\ 1.000 & 1.000 & 1.193 & 1.193 & 1.043 \\ 0.838 & 0.838 & 1.000 & 1.000 & 0.874 \\ 0.838 & 0.838 & 1.000 & 1.000 & 0.874 \\ 0.958 & 0.958 & 1.144 & 1.144 & 1.000 \end{bmatrix} \quad (3.16)$$

$$Eigenvector = \begin{bmatrix} 0.216 \\ 0.216 \\ 0.181 \\ 0.181 \\ 0.207 \end{bmatrix} \quad (3.17)$$

After this step, the calculated eigenvalues may be brought into the hierarchy structure, as shown in Figure 3.7.

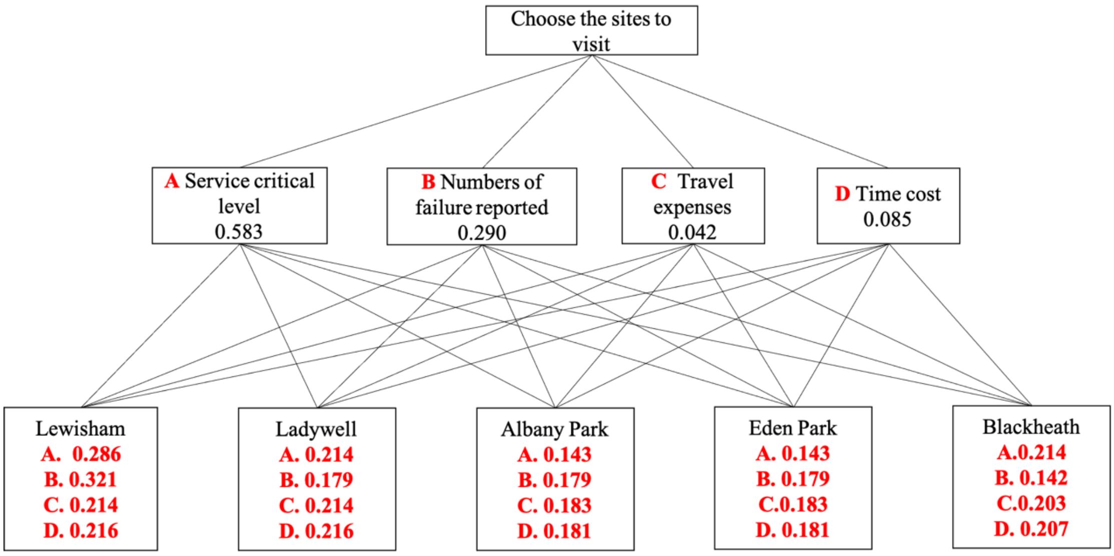


Figure 3.7 AHP with criterion and alternative priorities

The final ranking can be calculated as:

$$\begin{bmatrix} 0.286 & 0.321 & 0.214 & 0.216 \\ 0.214 & 0.179 & 0.214 & 0.216 \\ 0.143 & 0.179 & 0.183 & 0.181 \\ 0.143 & 0.179 & 0.183 & 0.181 \\ 0.214 & 0.142 & 0.203 & 0.207 \end{bmatrix} * \begin{bmatrix} 0.583 \\ 0.290 \\ 0.042 \\ 0.085 \end{bmatrix} = \begin{bmatrix} 0.287 \\ 0.204 \\ 0.158 \\ 0.158 \\ 0.192 \end{bmatrix} \tag{3.18}$$

This result shows that the weighting for Lewisham Station is 0.287, for Ladywell Station is 0.204, Albany Park Station and Eden Park Station have the same weighting of 0.158, and the weighting for Blackheath Station is 0.207. Based on the weighting results, it can be indicated that Lewisham Station, Ladywell Station and Blackheath Station are the top three most urgent for planning a site visit. It can be seen that MCDM is an effective tool to combine all criteria together to achieve a common goal.

3.4 Summary

This chapter first illustrates how SE was chosen as the main approach used in this study, to cope with complexity in the railway environment. It then identifies MCDM as an effective SE tool involving both quantitative and qualitative analysis. The aim of MCDM is to present a structured methodology to assist with decision-making when there is a lack of quantitative data in the early stages of system design. Another important advantage is the multi-criteria characteristics, making it appropriate for application to meet different aspects of requirements. Finally, a real railway industry example of choosing the site to visit has been given to demonstrate the step-by-step survey design and mathematical process of MCDM.

The application of MCDM to the criteria evaluation within the function allocation framework will be presented in Chapters 5 and 6.

CHAPTER 4 APPLICATIONS OF THE DECISION-MAKING FOR RAILWAY MAINTENANCE

Because of the complexity of railway maintenance systems and the fact that MCDM is ideally suited to solving problems with complex systems, Chapter 3 introduces MCDM as a method of decision making. From the analysis in Chapter 3, the authors can conclude that there are two important aspects in decision making for complex systems. The first is to list the evaluation criteria that may have an impact on decision making, and the second is to judge the relative importance of these criteria. In response to these two aspects, this chapter will focus on what factors may influence the function allocation in the automation of railway maintenance systems, and the relative importance of these factors.

Starting from the operating environment of RAS system, section 4.1 presents the author's analysis and definition of railway environment. Based on the railway environment features, the selection of evaluation criteria is elaborated from the perspective of definitions, analysis tools and railway application practices which is presented in section 4.2, section 4.3 and section 4.4. Finally, evaluation criteria are determined to support the function allocation decision.

4.1 Railway maintenance environment

Navigating the operating environment is one of the most crucial first steps for an RAS project [119][120]. The capability of interacting with the environment is essential for RAS to perform tasks such as grabbing, interacting with humans, and high-precision inspection. Therefore, a well-established RAS relies on accurate identification of the relevant real-world structure; the environmental navigation process is generally seen as the precondition of automation [121].

Despite the definition of the environment varying with the application, it can be summarised from the literature that environments are broadly divided into three categories: structured, semi-structured and open [122][123][124][19]. There is currently little research around railway maintenance environment categories; therefore, RAS environment definitions in other industries are discussed first, then the definition of railway maintenance is derived.

In the scenarios of autonomous driving [122], open environments are defined as vehicles that are not constrained and free to choose any path, such as in off-road driving. Highly structured environments are roads with a strong topological structure, and vehicles are constrained to drive on the graph, e.g., the highways or city streets. By contrast, semi-structured environments have topological drivable graphs, but they are previously unknown or may allow manoeuvres with deviation. A typical example is driving in a car park where the drivable lanes are constrained, but autonomous vehicles need to first sense their surroundings and make decisions such as avoiding other cars and looking for an available parking space.

In most cases, manufacturing production lines are considered as structured environments [77]. However, for robotics used in high-precision assembly [124], both real-time visual feedback and force control are mandatory to guide the robot to the desired position and orientation, as the related information such as position, force and robotic motions is known in advance, but not accurately enough for tight tolerance assembly. As a result, a precision assembly line is viewed as a semi-structured environment.

It can be concluded that a structured environment means that the surroundings are known with high certainty. As guidance, the information can be directly used to control RAS. On the contrary, unstructured environments represent completely unknown surroundings where RAS operations are totally dependent on real-time sensing systems. Operations in semi-structured environments are also known, but with unidentified variations and uncertainties. In these cases, real-time environment navigation would be necessary. Table 4-1summarises the mentioned environment definitions.

Table 4-1 Environment definition

Environment	**Definition**
Structured environment	The surroundings are known with high certainty. The information can be directly used to operate RAS with infrequent sensing.
Semi-structured environment	Surroundings are known, but with unidentified variations and uncertainties. Operations require the combination of known environment information and real-time sensing information.
Unstructured (open) environment	Completely unknown surroundings where the RAS operations are totally dependent on real-time sensing systems.

In a maintenance depot, the components to be inspected and repaired are diverse despite being manufactured to align with unified standards. An example is the wheelsets in a maintenance depot, as shown in Figure 4.1: although all wheelsets are roughly the same shape, there are infinite variations in the precise geometry of used/worn wheelsets and fault severity level. When performing an automated inspection, certain NDI technologies or vision systems require the surface geometry to be known with a high degree of accuracy; RAS must be capable of providing a collision-free path for inspection.

It can be noticed that although the railway maintenance environment is roughly known, there are uncertainties in terms of the accurate location of objects, status of components and diverse NDI precision requirements. Therefore, railway maintenance is defined as a semi-structured environment.

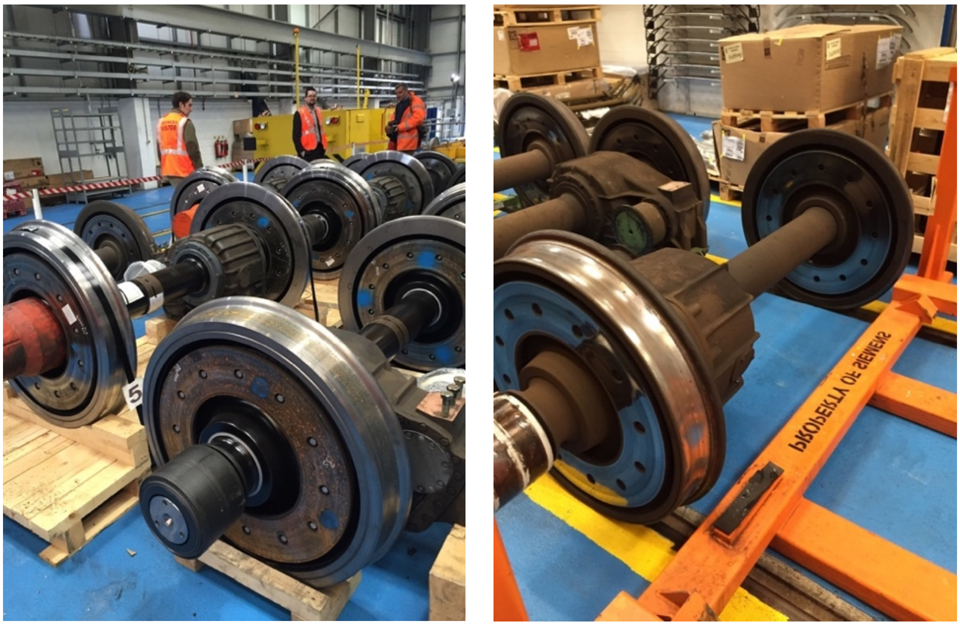


Figure 4.1 Wheelsets in Siemens depot, Northampton, 2016

As discussed in Chapter 2.6.2, the automation of railway maintenance and manufacturing needs to consider both physical and cognitive aspects. RAS has already been playing an increasingly important role in manufacturing production lines [77]. But currently, most applications in railway maintenance are limited in automated monitoring and inspection cases [125]; besides that, a number of them are only semi-autonomous which means human intervention is still required [126]. A substantial reason is that RAS normally works in a structured environment [127]; for example, the industrial robotic arm in manufacturing knows the relevant states of the surroundings with certainty and only needs to perform a few motions. Also, people are usually banned from the operation area when the robot is in motion [77]. Instead, when performing railway maintenance tasks in a semi-structured environment, a robot has to adapt to environmental uncertainty and deals with different failure modes [13]. Despite robust environment navigation and mapping methods developed for structured and static environments [120], coping with dynamic, semi-structured or unstructured environments still poses critical challenges [19]. In consequence, technological feasibility is an essential criterion in railway maintenance function allocation, which will be further discussed in section 4.2.

4.2 Technological feasibility analysis

In Chapter 2.5.2, it was stated that railway maintenance automation processes should be seen as the interaction between mechanisation and computerisation. Therefore, feasibility analysis in this study is considered from those two aspects.

Chiantella et al. [128] further illustrated that the automation of mechanisation is the replacement of human muscle power activities, e.g. assembly, lifting and handling tasks; on the contrary, automation of computerisation is the replacement of human sensory and mental activities such as information perception, analysis and decision-making.

4.2.1 Physical feasibility analysis

Typical physical activities in maintenance include manipulating, handling, lifting, assembling etc. H. Akrout et al. [129] proposed a two-stage task classification methodology to capture the basic physical motions required to achieve automated maintenance. It applies industrial engineering techniques (Therbligs and SIMO) to analyse complex maintenance tasks.

Therbligs were defined as basic elements of tasks by Gilbreth [130] (Table 4-2), aiming to improve manual efficiency within the workplace. They consist of a set of 18 basic motion elements; each element describes a standardised operation. The principle of Therbligs used in this example is to decompose maintenance tasks into basic unit motion elements. Therbligs could then be plotted onto a Simultaneous Motion (SIMO) chart to indicate the time required for each motion [131]. SIMO is a micromotion study proposed by Gilbreth; it graphically presents the precision motions of the limbs as well as the time taken for movements [132]. As shown in Table 4-3, an assembly motion is analysed by applying SIMO [133].

Successfully decomposing a task into the form of Therblig indicates the applicability of physical automation.

Table 4-2 Therbligs [132]

Search (Sh)	Use (U)	Find (F)
Disassemble (DA)	Select (St)	Inspect (I)
Grasp (G)	Pre-position (PP)	Hold (H)
Release Load (RL)	Transport Loaded (TL)	Unavoidable Delay (UD)
Transport Empty (TE)	Avoidable Delay (AD)	Position (P)
Plan (Pn)	Assemble (A)	Rest (R)

Table 4-3 SIMO example [134]

SIMO motion: assembly					
Left hand details	Therblig	Time (sec)	Time (sec)	Therblig	Right hand details
To grasp	G	5	6	G	To grasp
To upload	TL	9	8	TL	To upload
To search	SH	6	6	G	To grasp
To grasp	G	5	11	TE	To load
To hold	H	9	45	U	To weld
To upload	RL	8	8	RL	To upload

As illustrated in Figure 4.2, maintenance events are firstly recorded as videos, then Therbligs and SIMO methods are applied for detailed analysis.

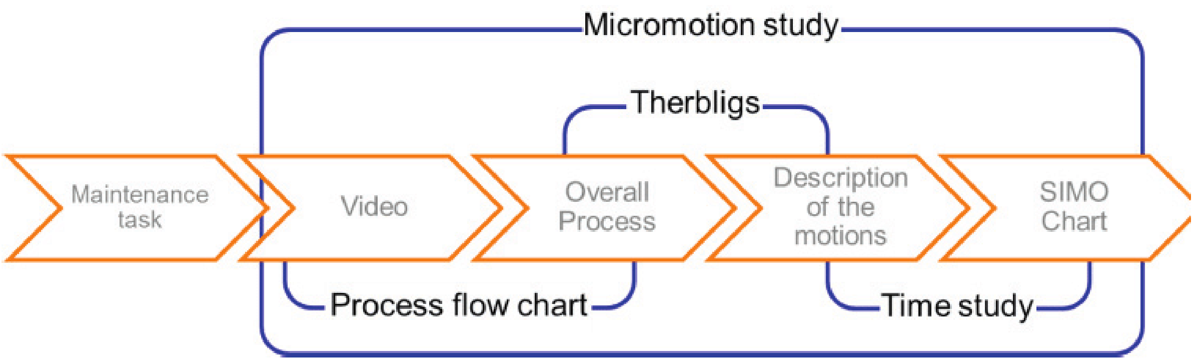


Figure 4.2 Task classification methodology [129]

Similarly, in robotics applications, the methods of motion decomposition are applied in analytical tools known as off-line programming [131]. There are a number of virtual software platforms that can help with the preliminary design of complex robot tasks. They are usually based on the 3D virtual representation of the real-world robot work cell. Users design the robot trajectories by selecting basic motions such as a linear move, a small arc of a curved path and a small angle of orientation. Robot parameters such as speed, delay and load can be set in the software by users. To ensure collision-free motion, path trajectories can be simulated before operating the real robot. Also, using virtual environments demonstrates the physical applicability of robotics. An example using a KUKA robotic arm will be presented in Chapter 6.

4.2.2 Cognitive feasibility analysis

For cognitive automation, R. Parasuraman and T. Sheridan [62] adopted a four-stage model for the human cognitive process, as indicated in Figure 4.3.

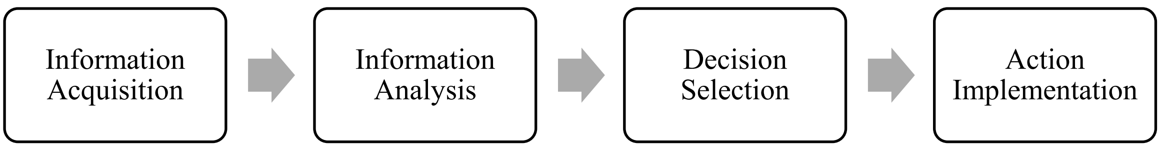


Figure 4.3 Cognitive stages[62]

Information acquisition coincides with human sensory activity; it consists of sensing and information registration. In railway maintenance applications, the automation of acquisition may include various sensing systems. For example, visual sensors installed on the end of an arm continuously acquire real-time data from the surroundings to guide robotic path-planning. DeltaRail UK developed an automated track-side system to inspect the under-vehicle components. It uses cameras and lasers mounted beneath the tracks to capture a series of images when the train passes over [134].

Information analysis corresponds to the memory and inferential processes of the human brain. Analysis automation has been rapidly advanced in various industries and applications. Automation at this stage involves techniques such as data storage, data integration, signal processing, simulation and prediction. An example is the real-time Visual Inspection System for Railway (VISyR) which is capable of detecting missing fastening bolts and other rail defects. After acquiring sufficient images for training, neural network classifiers can be applied to extract information and image classification for auto-detection [135].

Decision selection for humans is the process of evaluating and choosing among alternatives. Automation of decision selection involves augmentation or replacement of human brain activities with machine or computer decision-making algorithms. One example in maintenance is the expert system applied to assist with decision-making to improve the process of predictive maintenance, which significantly increases the confidence in making correct decisions, especially when information is incomplete or uncertain [33]. These techniques have also been applied to the rail domain, for example in the identification of faults in points operating equipment [136].

Action implementation is the actual execution of the choice. It can be seen as the connection between cognitive analysis and physical actions. Automation at this stage involves using RAS to replace humans to respond to the choice of actions. One example is an integrated control platform sending commands to control networked vehicle systems [137].

The above feasibility analysis proves that all types of sub-functions have the potential to be automated in railway maintenance systems. As mentioned, feasibility is the primary criterion to consider; however, one has to further evaluate a few more factors, taking into account the feasibility of the whole system: whether the entire system performance be improved or whether it is financially worth investing in. These problems will be discussed in the following sections.

4.3 System performance evaluation

A well-defined performance evaluation regime that meets the needs of different stakeholders is essential for maintenance process planning and optimising. Performance measures vary with different demands of the project and era. Since the beginning of the industrial age, engineers have been working towards improving the reliability of systems and equipment. As the complexity of equipment or systems rises, the costs and risks associated with failures become greater. Thus, it is increasingly significant to systematically assess safety and to predict the cost [138].

In the context of railway maintenance, the Italian Railway Network defined 'Reliability Availability Maintainability and Life Cycle Cost (RAM-LCC)' as the maintenance performance indicator (MPI) model. Similarly, Queensland Rail chose safety, reliability and cost as the MPI targets [139]. Reliability, Availability, Maintainability and Safety (RAMS) discipline was first proposed by the aerospace industry and has been widely adopted and applied to many other transportation areas, especially for safety-critical systems. It has also been facilitated in railway applications as a decision support for effective maintenance. For example, A. Patra and G. Simões applied RAMS to optimise rail track maintenance strategy

[140][141]. M. Park's work focuses on developing a systematic method for the integration of RAMS management into railway systems engineering [142].

From the perspective of RAS performance evaluation, D. F. Seifer et al. [143] selected safety and scalability as performance evaluation benchmarks for socially assistive robotics. M. L. Leuschen et al. [144] and B. S. Dhillon and N. Yang [145] all considered reliability as a crucial criterion, and S. Cheng and B. S. Dhillon [146] further put forward reliability, availability and safety as robot performance analysis factors. RAS is often used to assist or replace humans when the tasks are branded as the '4Ds' type: dangerous, difficult, dirty or dull [13]. A number of railway applications have already been developed, such as 3D printing of robots for railway maintenance and renewal optimisation [13] and a robotic inspection system for rolling contact fatigue cracks on railway tracks [147]. RAS shows great potential for better system performance in terms of increasing the repeatability of tasks (enhanced reliability) and freeing people from hazardous environments (improved safety) [148].

It can be summarised that RAMS analysis is applicable for both railway maintenance and RAS performance evaluation; therefore, it has been adopted for the present study as one of the evaluation phases. The next few sections will further discuss how RAMS analysis can be applied to railway maintenance systems.

4.3.1 RAMS in the railway context

British Standard EN 50126 [149] provides the interrelation of RAMS elements in railway systems, as shown in Figure 4.4.

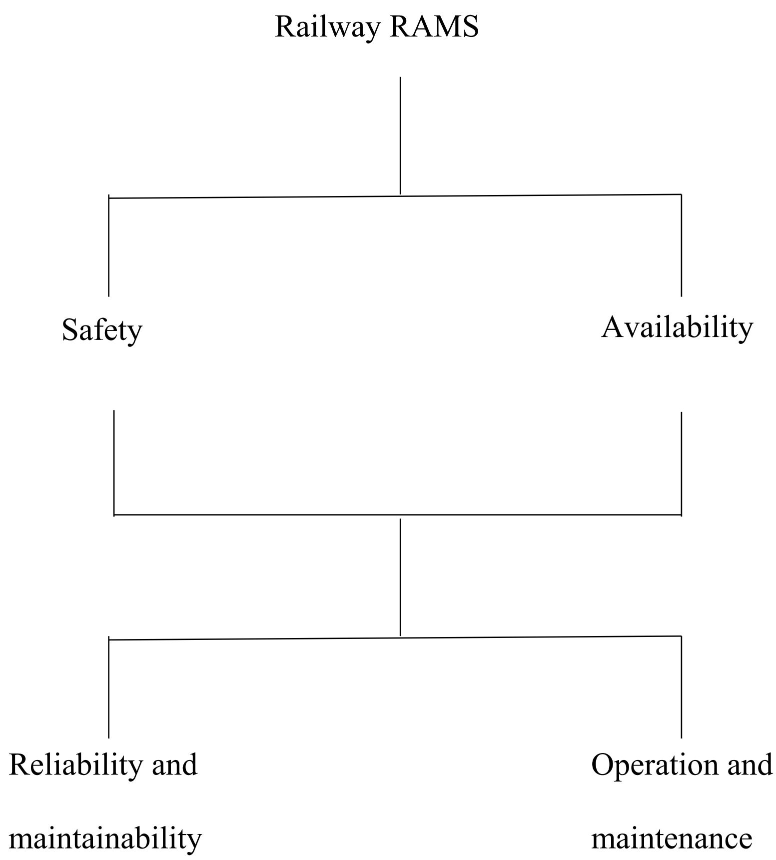


Figure 4.4 Railway RAMS

Figure 4.4 indicates that availability and safety are factors affecting the performance level of RAMS. Their measures are determined by reliability, maintainability and the inherent characteristics of the system. Reliability and maintainability are lower levels of RAMS elements, the same as operation and maintenance [150].

EN 50126[149] also defines RAMS as follows:

- **Reliability** is the probability a system or component will perform its required function, without failure under given conditions for a given time interval;
- **Availability** describes the probability of an item being in a state to perform a required function under given conditions over a given time interval;
- **Maintainability** is the probability of being retained in, or restored to, a state to perform as required, under given conditions of use and maintenance;

- **Safety** defines the freedom from unacceptable risk from harm.

It can be seen from the definitions that reliability, availability and maintainability all describe the probability of an item performing a certain action within a given time interval. Considered from the perspective of quantitative analysis, reliability is quantified as MTBF (Mean Time Between Failures) for repairable failures and MTTF (Mean Time to Failure) for non-repairable failures. Maintainability is quantified by the Mean Time to Repair (MTTR), and availability can be written as MTBF/(MTBF + MTTR) which indicates that availability depends on reliability and maintainability [150]. Hence, reliability, availability and maintainability (RAM) are considered together in the present study, and safety is discussed separately.

4.3.2 RAMS analysis tools

Assessing RAM is strongly based on failure analysis. From the definition of RAM[149], reliability is related to the probability of failure in a given time interval, in terms of:

- Possible failure modes within maintenance;
- Rate of each failure modes;
- The consequences of each failure.

Maintainability is defined as the probability that an item can be repaired in a given time interval, in terms of:

- The frequency of the performance of maintenance;
- Time for the detection of faults;
- The time it takes to repair the system after a failure.

It can be seen that failures directly determine the reliability (the probability and rate of failure modes) and maintainability (the frequency of failures occurring in a given time interval) of the system. Therefore, the most common used RAM analysis tools in railway, for example, Failure

Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), the Reliability Block Diagram (RBD) and the Markov method, are all based on failure analysis.

FMEA was introduced in the 1940s for human errors and product failure assessment [151]. It is a systematic analysis tool performed at the component level. Typically, FMEA starts with potential failure and then tracks the effects until the end consequences. The analysis process includes identifying possible failure modes, potential causes and associated risks. FMEA is widely applied to assess the performance of railway systems, for example, railway turnouts [152], signalling systems [151], wheels and axle boxes [153].

Different from FMEA, FTA is a top-down method. It intends to figure out how a system fails and helps to propose the best way to avert risk. FTA attempts to identify all logical paths leading to undesired events from top to bottom. Quantitative FTA calculates the probability of a system failure [154]. FTA is an effective and accurate analysis tool at the systemic level, and has been widely applied in complex systems [155].

Both FMEA and FTA can be used for RAM assessments. M. Park [142] stated that individual techniques may not meet the performance evaluation demands of an entire complex railway system, and an integrated FMEA-FTA approach is proposed. Similarly, M. Rausand and A. Høyland [156] also suggested that during RAMS analysis, FMEA is an essential first step to understand the potential failures before applying FTA for a systematic analysis. Chapter 6 presents an application for maintenance system analysis.

There are methods usually used complementarily to optimise the analysis process. For example, RBD focuses on investigating how the reliability of each component would contribute to the failure of the whole system. It provides a straightforward block presentation of the system components and also illustrates the network relationship of a complex system [157]. Considering human error in maintenance, the Markov method is the main approach to predict the probability of system failing due to human errors [158].

Safety is defined as 'the freedom from unacceptable risk of harm' [149]. To help support safety-related decisions in railway systems and beyond, the RSSB issued 'Taking Safe Decisions' which suggests a risk-based monitoring method for safety management [159]. The Office of Rail and Road (ORR) published the Common Safety Method for Risk Evaluation and Assessment (CSM RA) [160] which specifies a risk management process that must be applied to a railway system in the event of any significant changes. Risk assessment is a widely recognised tool for assessing safety in the railway industry.

According to RSSB Guidance Note GEGN8684, the related definitions are:

Risk analysis is the systematic use of all available information to identify hazards and to estimate risk.

Risk evaluation is a procedure based on the risk analysis to determine whether an acceptable level of risk has been achieved.

Risk assessment is the overall process comprising a risk analysis and evaluation.

FMEA and FTA are also commonly employed risk assessment tools for both railway maintenance and RAS [161][162][163][164].

RAMS is selected as one of the evaluation criteria to help make function allocation decisions from the perspective of performance evaluation. The definitions, relations and analysis methods of RAMS are introduced. FMEA and FTA are specifically discussed as they are adopted for both RAM and safety analysis which will be further discussed in Chapter 6.

4.4 Cost analysis

The evaluation of RAMS will help to determine the different automation alternatives of the maintenance system. As stated in Chapter 2.4, reduced cost is one of the major demands for maintenance. The cost analysis will help optimise the cost-efficiency of maintenance operations from RAMS analysis.

4.4.1 Cost estimation

Costs are the sum of the funds required to achieve the expected project outcome. Cost estimation is required for predicting the cost at the preliminary system design stage [165]. W. J. Blanchard and B. S. Fabrychy [18] indicated that with an increase of system complexity, not only the associated investment cost but also the operating costs would increase alarmingly.

The European Commission [115] suggested that in determining the cost of a transport project, three aspects should be considered: total investment costs, total operating/maintenance costs and asset replacement costs.

To ensure coverage of all project phases, life cycle cost (LCC) is widely used in the railway industry for cost estimating or analysis [166][167]. It is the estimated sum cost of a particular solution considered throughout the life of the system. It typically contains both planned and unplanned investment costs plus any ongoing operation and regular maintenance costs [168].

Figure 4.5 illustrates a railway system LCC. S. Wollny [167] pointed out that the cost estimation of a railway system would consist of investment, operating and maintenance costs. This LCC model is linked to the present study since it estimates the cost over the life of a railway system, applicable for both human and RAS systems.

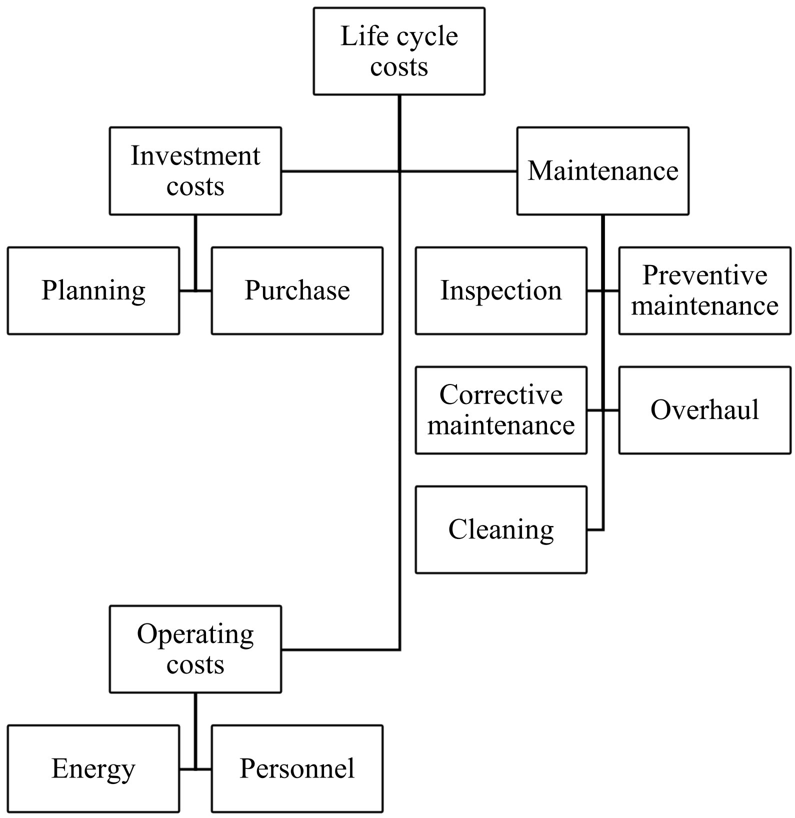


Figure 4.5 Railway LCC [56]

Blanchard and Fabryky [18] discussed LCC from a system perspective; the activities of concern associated with LCC during each stage of a system's life are shown in Figure 4.6. It indicates that the LCC of a system needs to be considered from system planning to the cost of disposal support. Cost estimations can provide implications for maintenance actions over the service life of the system, instead of only short-term predictions. Asiedu and Gu [169] pointed out that different life cycle phases will be paid for by different organisations (company, user and society), as shown in Table 4-4.

For example, when estimating the use of robotic arms in a maintenance depot, LCC would cover the procurement, usage and disposal costs, which may involve costs of purchase, transportation, storage, maintenance and recycling.

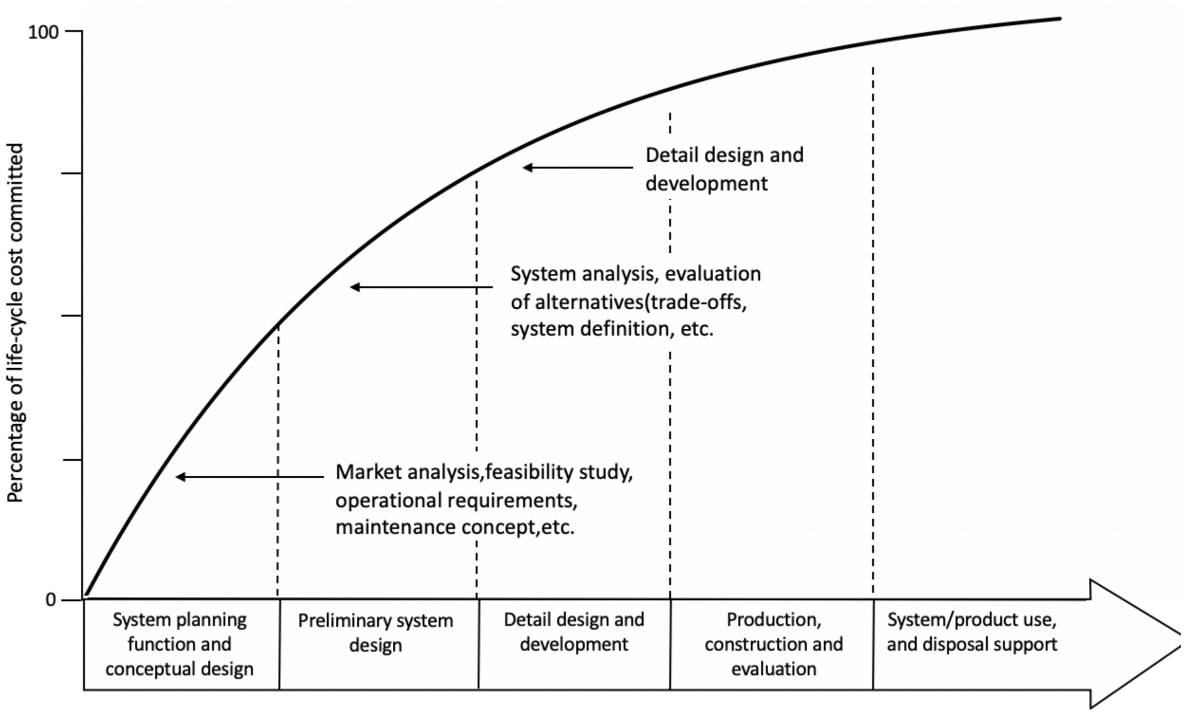


Figure 4.6 Activities affecting LCC [18]

Table 4-4 Life cycle stages and costs [170]

	Company cost	**User cost**	**Society cost**
Design	Market recognition development		
Production	Materials, Energy, Facilities, Wages, Salaries etc.		Waste, Pollution, Damage to health
Usage	Transportation, Storage, Waste, Breakage, Warranty service	Transportation, Storage, Energy, Materials, Maintenance	Packaging, Waste, Pollution, Damage to health
Disposal/recycling		Disposal/recycling	Waste, Disposal, Pollution, Damage to health

4.4.2 Cost analysis methods

Cost estimating aims to generate an accurate prediction of LCC. Cost analysis methods are then applied for decision support on cost. This section gives cost analysis examples for RAS and railway practices respectively.

P. Gekas and K. Perera suggested calculating the payback period when considering the investment of robotics systems [170]. The payback period is used to determine the time required to recover the original investment. It is an important tool for evaluating whether the investment made has an acceptable recovery time [171]. The shorter the payback period, the more attractive the investment. The payback period can be calculated as:

$$Payback\ period = \frac{Total\ investments}{Total\ yearly\ savings} \tag{4.1}$$

Cost-benefit analysis (CBA) is an important economic analysis method applied in railway systems [115][117]. It is one of the most effective decision-making tools applied in the early design phase for economic assessment which provides a systematic approach to identify and quantify anticipated costs and benefits, followed by a trade-off evaluation to help make an investment decision [165]. CBA helps to foresee the actual total cost and quantify the benefits within a system. The goal is not to minimise the cost, but to achieve the optimal balance among different performance criteria and cost.

Maintenance cost is one of the main concerns for train operating companies and other stakeholders [172]. Hence, cost is selected as another criterion and cost analysis is integrated as part of the evaluation process.

4.5 Summary

This chapter focuses on the criterion selection for railway maintenance function allocation decision problems. The characteristics of railway maintenance show a semi-structured environment where operations are constrained with uncertainty which poses a technical challenge; therefore, feasibility is derived as the primary criterion. Physical feasibility analysis is beneficial by using virtual simulation and task classification techniques. Furthermore, multi-stage cognitive analysis provides essential information for determining the level of system automation.

In addition, the evaluation of system performance is crucial at the early stage of preliminary maintenance system design. RAMS is selected as the measure of performance; these criteria would become helpful in ensuring the overall system performance improvement of the final man–machine system.

Finally, to achieve a cost-efficient system, cost analysis methods are discussed in this chapter. In summary, an evaluation of these three phases criteria (feasibility, system performance and cost) will be given in Chapters 5 and 6.

CHAPTER 5 RAILWAY MAINTENANCE FUNCTION ALLOCATION FRAMEWORK

As stated in section 1.3, there is a demand for a novel framework capable of integrating requirements from various aspects. Based on the function allocation theories reviewed in section 2.5, Chapters 3 and 4 illustrated the MCDM process and criteria selection, respectively. This chapter demonstrates the design of the novel railway maintenance framework which forms the core of this work.

The proposed framework is focused on providing comprehensive guidance for railway maintenance function allocation to aid system design, as illustrated in Figure 5.1.The framework consists of three parts.

1. Problem decomposition and task analysis

Includes the boxes "current maintenance requirements", "task analysis" and "preliminary allocation" in Figure 5.1.

2. Iterative evaluation and allocation

Includes the boxes of process 1,2,3 and primary, secondary, tertiary evaluation criteria in Figure 5.1.

3. System design, which the final function allocation

Section 5.1 will explain the collection of maintenance information, task analysis and how tasks map with ergonomic analysis. Section 5.2 will detail the function evaluation, and iterative and decision processes. As discussed in Chapter 4, the author has taken into account a variety of factors unique to railway maintenance and has finally decided on three levels of evaluation criteria. In Figure 5.1,the primary evaluation criterion is feasibility, the secondary criterion is system performance, and the last issue that needs to be considered in the function allocation framework is cost.

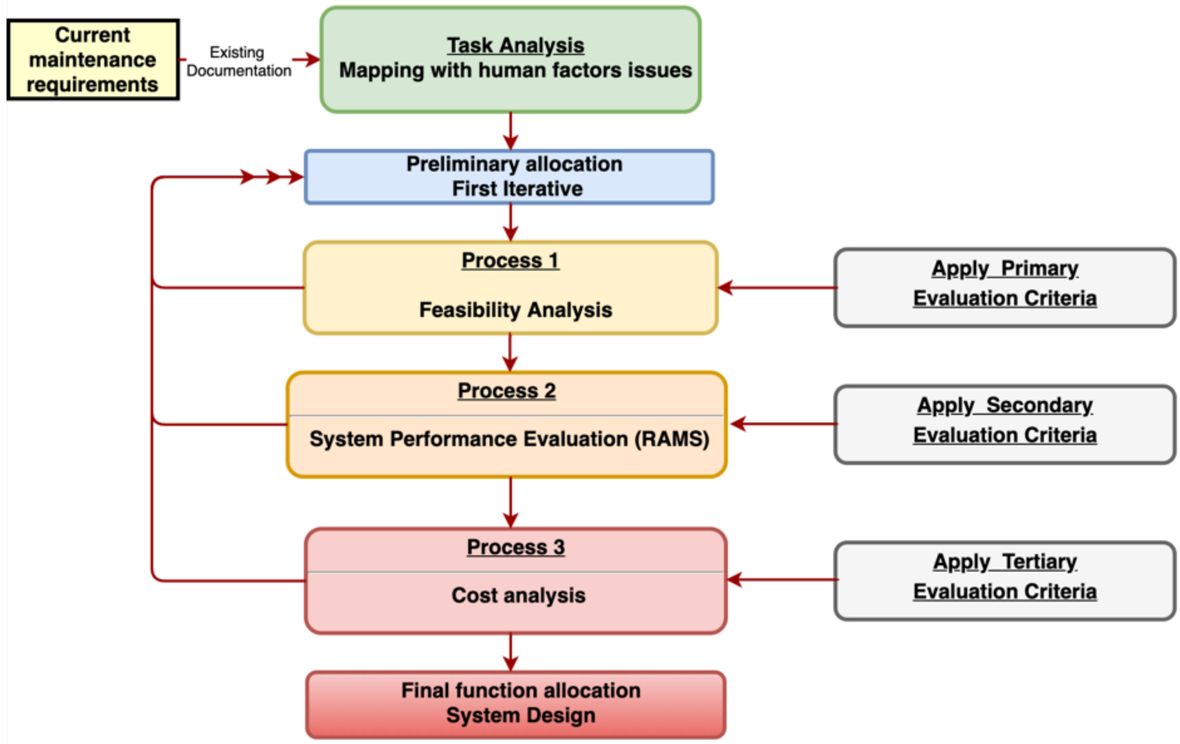


Figure 5.1 Railway maintenance function allocation framework

5.1 Problem decomposition and task analysis

Understanding maintenance activities unambiguously is a prerequisite for automatic decision making; therefore, a comprehensive information collection process is designed as the input of the framework, which could include a maintenance activities checklist, failure modes, sensing technologies, tolerance specifications and guidance for maintenance actions. Suggested sources for information collection are listed below:

1. Reference information on railway maintenance, such as reports published by the RSSB, and International/European or British Standards related to railway maintenance.
2. Reference to related academic publications.

3. Maintenance manuals and instruction documents such as vehicle maintenance instruments (VMIs).
4. Site visits, observations.
5. Questionnaires and workshops to incorporate specialist knowledge/experience.

Since the railway environment and components are complex, it is usually unrealistic to make a decision directly on the automation of the entire system or complete tasks. Railway maintenance systems consist of various components, sub-system interactions, operations and stochastic activities and have specific standards to comply with [173]. The RSSB considers task analysis as a key step in function allocation as it helps to understand the procedures and characteristics of a task or the behaviours involved with operators [174]. Task analysis is an effective tool for breaking down a high-level task into multiple sub-tasks, seeking to accomplish highly detailed task procedures. In this way, operators would clearly realise which tasks to perform, how to perform them and in what order. Therefore, task analysis would be an appropriate analysis step following the collection of information.

In addition, the framework also intends to integrate ergonomic features into the task analysis procedure. The criteria presented in Chapter 4 are primarily based on technical features, system performance and related costs. However, automation may alter the task structure and the feedbacks sent to operators. Hence, automation solutions often dramatically influence human operators in a system [175]. Moreover, as stated in section 1.1, one important motivation to automate maintenance in this study is reducing human errors, freeing humans from dangerous working environments and eliminating monotonous repetitive tasks. Therefore, it is necessary to take ergonomics into consideration. Section 5.2 will present a detailed task ergonomic analysis, including a wheelset maintenance example.

The ultimate goal of task analysis is to examine ergonomics for sub-tasks and to derive the preliminary function allocation decisions as the initial information is passed to the further three evaluation phases. Consequently, sub-tasks are initially labelled as either wholly manual or with potential for automation. Then, the allocated tasks are fed into the full framework process. As reviewed in section 2.6, there are two options for automation design. One is to automate everything, with humans left to perform functions which are too expensive or infeasible to automate. The other option is to match human and machine capabilities; functions indicated as being done better by machines would be automated, whereas functions which humans perform better would not [62]. It is worth noting that the latter method is adopted in this framework. Therefore, the overall system would not benefit more from automating the tasks which were originally allocated to humans as they would inherently perform them better. As a result, the next steps will not consider the tasks labelled as wholly manual, but only put the focus on the tasks suggested for application of automation.

The preliminary allocation derived from task analysis is regarded as the starting point of the framework; the initial guess of allocation so far is done purely considering ergonomic issues. After generating the preliminary allocation, for each sub-task, designers assess the three key criteria (feasibility, system performance and cost as selected in Chapter 4) in sequence. If any evaluation determines that the sub-task does not meet the criteria, the process terminates immediately; certain sub-tasks will be labelled as manual, and remaining tasks will return to the task analysis phase to be re-allocated.

On the other hand, if all the evaluation processes are passed, the sub-task will remain the same as the preliminary allocation. System engineers can reach a final function allocation system design upon complete assessment of all the sub-tasks. The function allocation evaluation process will be elaborated in section 5.2.

5.1.1 Task analysis

In theory, task analysis is not a specific scientific principle, but a methodology for systematically collecting and recording task information used for describing and analysing complex tasks [176]. It is an interdisciplinary technique which is widely used in industrial engineering and ergonomics study; in this framework, task analysis is implemented in the following two phases.

1. Before tasks enter the evaluation iteration: tasks are decomposed into sub-tasks to enable further allocation decisions. Both human and machine capabilities are considered to ensure a feasible collaboration between human and machine (section 5.2).
2. During evaluation iteration: if the allocation decisions cannot meet any of the criteria (feasibility, system performance and cost), certain functions will go back to the task analysis step to be re-allocated (this will be discussed in section 5.3).

Drury [177] proposed two stages involved in task analysis: " description " and "analysis ". The former involves various types of descriptions such as operations sequence diagrams, man–machine charts and flow process charts to provide a clear statement describing the system operation procedures, task requirements and goals. On the other hand, the task analysis stage takes a step further by giving insights into the task demands, operator capabilities and likely errors. At this stage, tasks are further decomposed or re-expressed depending on different requirements. This two-stage method effectively integrates the information collection, decomposition and analysis of tasks; thus, it is applicable to complex systems such as railway maintenance. Hence, task analysis in this study also consists of description and analysis stages as illustrated below.

5.1.2 Railway maintenance task description

Task description is a set of clear methods for capturing a task at an appropriate level of depth. Drury [177] further stated that there are basically three types of description format. In general, ***sequence description*** is applied where a task has a rigid pattern and a limited number of choices, e.g., the start-up procedures for a piece of equipment. By contrast, ***branching description*** is adapted to tasks where actions are largely dependent on the outcome of previous sub-tasks. For example, inspection tasks would trigger actions if a failure were detected. ***Process control*** is suitable for scenarios where operators are required to continuously manage several variables using flexible strategies based on conditions such as stock trading. Considering the features of the railway maintenance environment, for example, composing of many sub-systems that interact with each other; branching description would be a more appropriate description format. A typical example of the task description is off-vehicle wheelset maintenance. Referring to Railway Group Standard GM/RT2466: Railway Wheelsets (published by RSSB [178]), off-vehicle wheelset maintenance-related tasks consist of:

- Handling, care of wheelsets and cleaning
- Wheelset condition assessment
- Tread measurement
- Overhaul
- Reprofiling, if required
- Assembly of wheels and bearings, if required
- Protection against corrosion
- Final check for conformity of the wheelset to standard requirements
- Traceability

Since the task decomposition procedures are similar, only the wheelset condition assessment will be further discussed as an example. According to the Laing O'Rourke wheelset inspection guidance [179] and observations made during maintenance depots visits by the author, condition assessments typically include general and complete inspections. The former is normally done visually prior to commencing operations. The general inspection of wheelsets requires technicians to identify if there are any signs of cracks, wheel flats, corrosions or imperfections. As a result, the inspection results can assist operators in deciding whether the wheelsets are to be released for service, abandon, repaired or sent to the workshop for a complete check with additional inspection tools (NDI). Generally, it is not adequate to assess the condition of a wheel by visual inspection alone during a complete inspection; thus, NDI as reviewed in section 2.3.2 is used to determine the presence of defects. Figure 5.2 shows the branching description of wheelset maintenance tasks derived from GM/RT2466 [178]. Figure 5.3 presents the task decomposition process of general inspection.

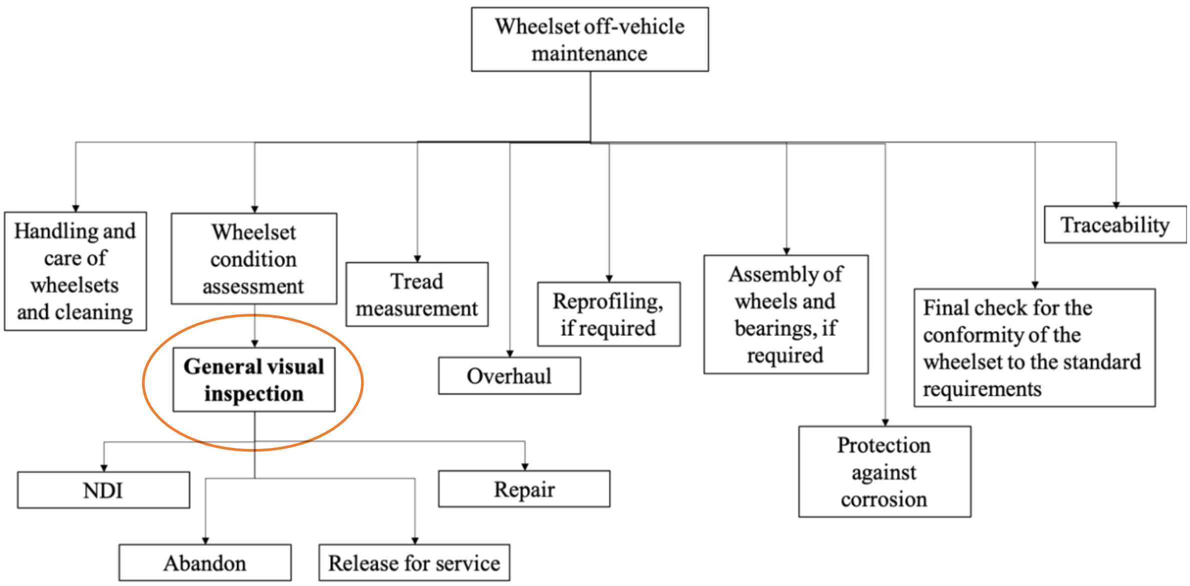


Figure 5.2 Wheelset maintenance task description[178]

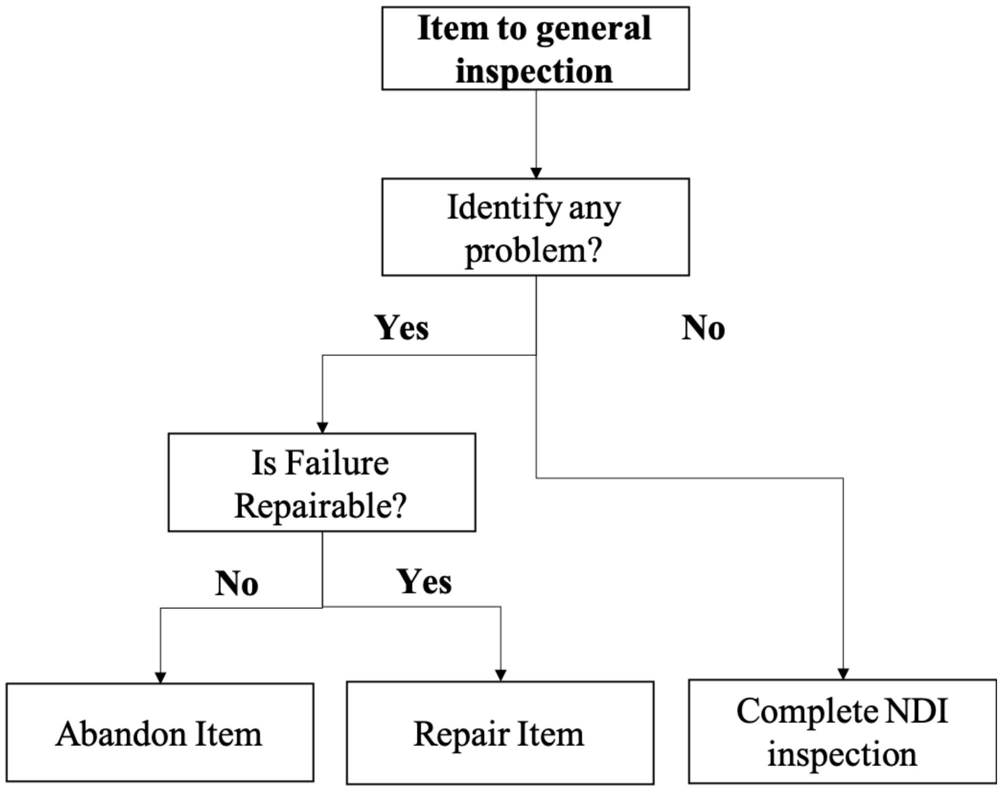


Figure 5.3 General inspection task description

5.1.3 Railway maintenance task analysis

Following the task description stage, this section illustrates the analysis step using general (visual) inspection as an example. Inspection was originally defined as a deliberate, in-depth and exacting process of a careful, precise and critical examination, in particular for flaws in a system [180]. In fact, visual inspection is more than merely walking around and checking. It requires the integration of visual detection and mental processing, such as concentration, information transmission and memory [181]. With the application of ergonomic analysis, Drury [182] summarised that there are five key steps involved in a general visual inspection task: Set-up, Present, Search, Decide and Respond.

Set-up includes the activities to identify the inspection objects, equipment needed for inspection and inspection procedures/instructions. **Present** involves the preparations for inspection, for example, system build-up and equipment installation. **Search** is examining items for any defects, flaws, etc. Then, inspectors compare the abnormalities with standards to **decide** whether they exceed the acceptable level. **Respond** actions are to accept, repair or abandon the items based on the decision.

In addition, among these five steps, Drury [183] argued that Search and Decision are the two steps with the highest probability of the occurrence of errors. This indicates that Search and Decision are the two most critical functions for human errors and directly affect the overall visual inspection performance, and special attention should be paid when performing related task analysis. Drury also listed the possible errors associated with each step (Table 5-1).

Table 5-1 Generic functions and errors for visual inspection, reproduced from [182]

Function	Expected outcomes	Logical errors
Set-up	Inspection equipment functional, correctly calibrated and capable	1. Incorrect equipment 2. Non-working equipment 3. Incorrect calibration 4. Incorrect or inadequate system knowledge
Present	Item presented to the inspection system	1. False item presented 2. Item mispresented 3. Item damaged by a presentation
Search	Indications of all possible nonconformities detected and located	1. Indication missed 2. False indication detected 3. Indication mislocated 4. Indication neglected before decisions
Decide	All indications located by Search correctly measured and classified, correct outcome decision reached	1. Indication incorrectly measured/confirmed 2. Indication incorrectly classified 3. Wrong outcome decision 4. Indication not processed
Respond	The action specified by outcome decision is taken correctly	1. Non-conforming action taken on conforming item 2. Conforming action taken on non-conforming item 3. Action incomplete

Based on the task description and combined with Drury's five steps theory, wheelset visual inspection steps can be summarised as shown in Figure 5.4.

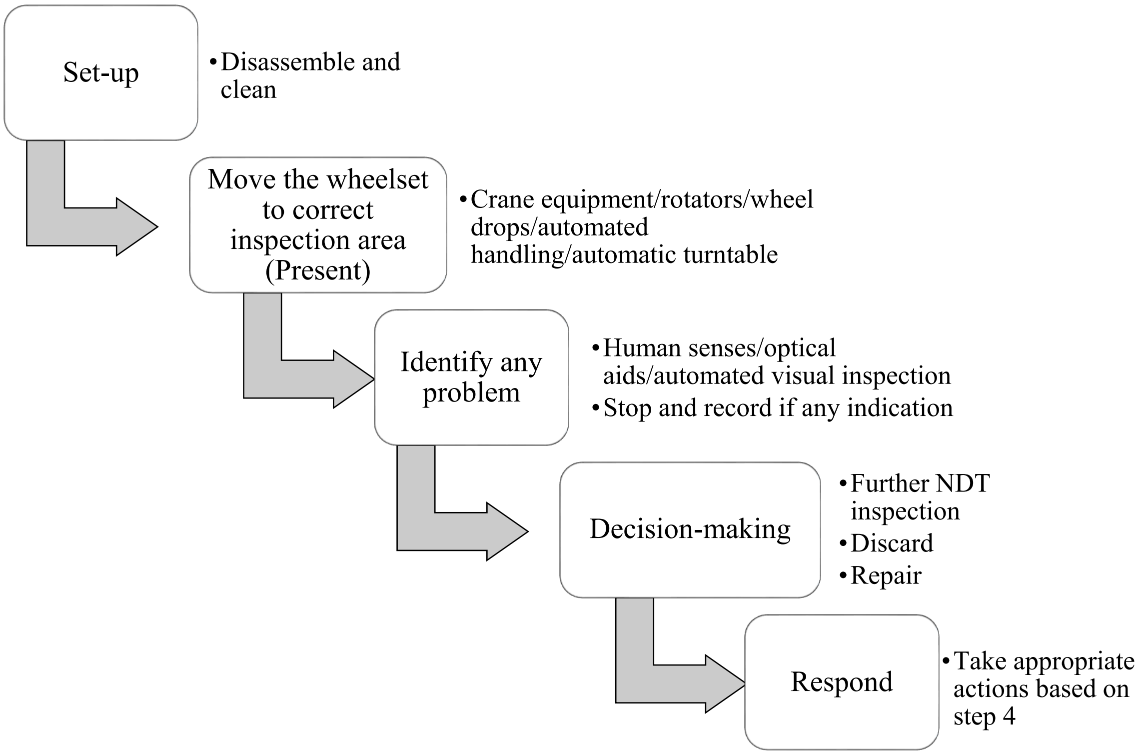


Figure 5.4 Visual inspection task steps[182]

The steps in Figure 5.4 can be described as follows.

1. Set-up (disassemble and clean)

   When the trains arrive at the maintenance depot, the wheelsets are disassembled and cleaned.

2. Move the wheelset to the correct inspection area (Present)

   This step involves manipulation of a relatively heavy load. There exists support equipment to help, such as crane equipment, rotators, wheel drops and automated handling.

3. Identify any problems (Search)

   Inspect the wheelset components to identify any problems (such as cracks, defects, corrosion or loose parts) and record any abnormality.

4. Make decisions (Decide)

   Following the inspection results, decide whether the severity level of failures exceeds the tolerance of relative maintenance specifications. Then determine whether the components need a further detailed NDT inspection or to be repaired or discarded.

5. Respond

   Based on the decision in step 4, take appropriate actions.

After the task decomposition stage, the next step would be mapping these sub-tasks with updated Fitts lists (Table 5-2) to derive the preliminary allocation. The Fitts list is a famous mechanism to determine whether humans or machines would perform a certain function better, aiming to optimise the distribution of functions between the two. As reviewed in section 2.6.1, in spite of criticisms such as it giving a too general description and its limitations in fitting dynamic environments and practical engineering design, the Fitts list has persisted throughout the history of function allocation [26]. It has been applied to both cognitive and physical tasks, concerned with the fact that automation would change the nature of tasks. It also recognises the importance of human capabilities. These advantages would make it suitable in the preliminary stage of railway maintenance allocation. However as reviewed and discussed in Section 2.6.1, with the advancement of technology, the author agrees that at present, humans apparently consider that machines surpass humans in detection, perception and long-term memory. In summary, an updated Fitts list will be applied in this framework.

Table 5-2 Updated Fitts list [68]

Humans are better at	**Machines are better at**
Ability to improvise and use flexible procedures.	Ability to detect small amount of visual or acoustic energy. (Updated)
Ability to reason inductively.	Ability to perceive patterns of light or sound. (Updated)
Ability to exercise judgement.	Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time. (Updated)
	Ability to respond quickly to control signals, and to apply great force smoothly and precisely.
	Ability to perform repetitive, routine tasks.
	Ability to store information briefly and then to erase it completely.
	Ability to reason deductively, including computational ability.
	Ability to reason handle highly complex operations, i.e., to do many different things at once.

Table 5-3 lists the visual inspection functions, corresponding capabilities required to perform the function, how these capabilities are allocated in the updated Fitts list and, finally, gives allocation suggestions which is the initial allocation as the starting point of the iterative process.

Table 5-3 Fitts list integrated into visual inspection task analysis

Function	Tasks	Related human/machine capabilities in Fitts list	Preliminary allocation
Set-up	When the trains arrive at the maintenance depot, the wheelsets are disassembled and cleaned.	Improvise and use flexible procedures (**Human**) Apply great force smoothly and precisely (**Machine**) Perform repetitive routine tasks (**Machine**) Ability to reason and handle highly complex operations (**Machine**)	Both machine and human involved
Present	Move the wheelset to the correct inspection area. This step involves manipulation of a relatively heavy load. There exists automatic equipment to help such as crane equipment, rotators, wheel drops and automated handling.	Apply great force smoothly and precisely (**Machine**) Perform routine and repetitive tasks (**Machine**)	Machine
Search	Inspect the wheelset components to identify any problems (such as cracks, defects, corrosion, loose parts) and record any abnormality.	Ability to detect a small amount of visual or acoustic energy (**Machine**) Ability to perform repetitive routine tasks (**Machine**) Ability to reason inductively (**Human**)	Both machine and human involved
Decide and respond	Following the inspection results, decide whether the severity level of failures exceeds the tolerance of related maintenance specifications. Then determine whether the components need a further detailed NDT inspection or are to be repaired or discarded. The action specified by outcome decision is taken correctly.	Ability to reason inductively (**Human**) Ability to exercise judgement (**Human**) Ability to reason deductively, including computational ability (**Machine**)	Both machine and human involved

Above all, the preliminary function allocation is that all sub-tasks could have automation introduced into them.

5.2 Function allocation iterative process

With the task analysis explained in section 5.1, primary, secondary and tertiary criteria were selected as feasibility, system performance and costs, respectively; also, corresponding analysis methods are covered in Chapter 4. This section will put a focus on the evaluation process and task re-allocation. The tasks within wheelset visual inspection will be used again for a clear illustration.

As presented in Figure 5.1, the evaluation process is interpreted as follows.

1. Start from the preliminary function allocation derived from the task analysis step;
2. Apply primary (feasibility) evaluation criteria;
3. IF the first criterion is met, apply secondary (system performance) evaluation criteria, ELSE, go back to be re-allocated (section 5.2.1);
4. IF the second criterion is met, apply tertiary (cost) evaluation criteria, ELSE, go back to be re-allocated (section 5.2.2);
5. IF the third criterion is met, determine the final allocation, ELSE, allocate as manual the tasks which are too expensive to implement;
6. Final function allocation and system design.

5.2.1 Feasibility analysis

Due to the unique characteristics of railway maintenance such as semi-structured environments and complex systems, the functions regarded as RAS would inherently perform better but might not be technically feasible. As mentioned in section 4.2.1, task analysis is applied to decompose a certain task into basic elements (Therbligs) to verify physical feasibility as machine can perform the basic Therbligs and the combinations of Therbligs. It considers the cognitive feasibility for four types of functions: information acquisition, information analysis, decision selection and action implementation.

One example is the search step in visual inspection, described as *'Inspect the wheelset components to identify any problems (such as cracks, defects, corrosion, loose parts) and record any abnormality'*. The premise of this step is that the wheelset has been moved to the correct inspection area. Feasibility requirements may vary with scenarios. Table 5-4 lists one possible feasibility requirement during automatic inspection.

Table 5-4 'Search' step feasibility requirements

'Search' step in automatic visual inspection	*Inspect the wheelset components to identify any problems (such as cracks, defects, corrosion, loose parts) and record any abnormality.*
Physical elements	Move the visual aids probe along the wheelset and ensure collision-free path during the inspection.
Cognitive elements	Information collection: Achieve a specific level of precision and be capable of continuously monitoring. Information analysis: Analysis of visual information, record any failure indications. Decision and action: fault diagnosis.

It can be recalled that the framework requires sub-tasks for further decomposition to assess feasibility. In this evaluation phase, if any of the elements are considered to be physically or cognitively infeasible, the task will be re-allocated as non-automated. For instance, if RAS cannot ensure a collision-free inspection path but is capable of cognitive tasks, then the physical tasks will be assigned to humans, which means the final system design is manual with visually aided probes for data collection and automatic data analysis. As a result, the system would be considered as semi-automatic.

5.2.2 RAMS analysis

At this secondary criteria evaluation stage, all functions are viewed as technically feasible. Another important consideration is whether applying automation could improve system performance.

Methods for respectively estimating and evaluating RAMS have been introduced in section 4.3. However, one important issue left over is that the overall system performance is determined by four criteria, and the criteria do not influence the overall system equally. Hence, there is a need to determine the relative importance of each criterion and derive criteria weightings. In addition, a comparison needs to be made between automatic and manual systems. Then, the allocation should be revised correspondingly in order to achieve better system performance.

Based on the above analysis and discussion in Chapter 4, RAMS evaluation phases can be identified as an MCDM problem. If the AHP method is applied as introduced in Chapter 3.3, the evaluation phase can be re-expressed as:

Goal: Choosing the system with better performance.

Criteria: Reliability, availability, maintainability and safety.

Alternatives: Manual system and automatic system.

The AHP for RAMS is presented in Figure 5.6.

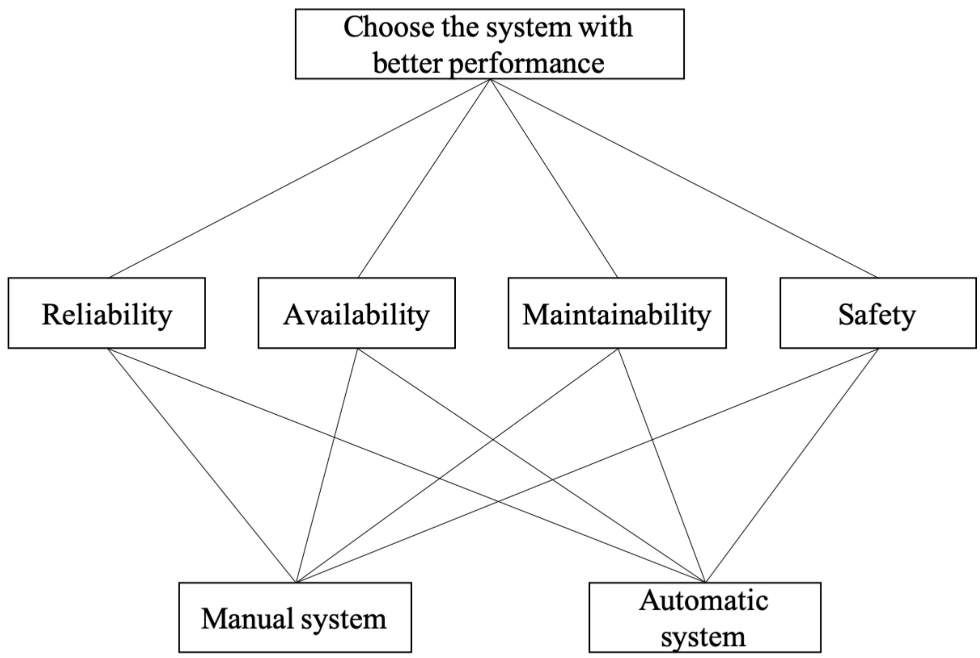


Figure 5.5 Use of MCDM for RAMS evaluation

If the MCDM indicates that a manual system would perform better, then tasks will be re-allocated to humans. There is a great variety of RAS; performance evaluation would be different accordingly. An example which makes use of RAMS analysis, based on an automatic robotic cell case study, will be presented in Chapter 6.

After the first two evaluation processes, the automatic functions are proved to be feasible and could provide better system performance; cost analysis is the final evaluation phase. If achieving automation is not financially worth investing in, then the functions will be allocated to humans. CBA has been introduced in Chapter 3, and cost estimation and analysis have been presented in Chapter 4. Cost analysis of a robotic cell will be included in Chapter 6.

5.3 Summary

In this chapter, a function allocation framework has been designed to meet the demands for railway maintenance.

A clear and in-depth description of a task is crucial for using the framework. It has been demonstrated that the branching description approach is more suitable considering the complex interactions and dependencies among the maintenance sub-tasks. The initial step of the framework also integrates human-factor elements into the task analysis process for generating preliminary allocation. At the evaluation stage of the framework, feasibility, RAMS and cost should be carefully assessed. RAMS can take advantage of the MCDM approach for reallocating tasks.

The proposed framework is designed as an iterative evaluation process by assessing a task using the three essential criteria (feasibility, system performance and cost) sequentially. Decomposed sub-tasks should pass all three processes to qualify for automation. Otherwise, they return to the preliminary allocation and will be classified as manual. The final system would be either fully manual, a mix of manual activities with well-defined automated elements, or a fully automated system.

CHAPTER 6 AUTOMATIC WHEELSET MAINTENANCE CASE STUDIES

Wheelset maintenance accounts for a significant proportion among various rolling stock maintenance actions. As wheelset failures normally require repair/replacement at short notice to avoid serious accidents, they are one of the most safety-critical components of both passenger and freight vehicles [184]. Wheelsets are also costly to maintain, and their failure may affect the operation of other vehicle components or mechanisms, resulting in additional cost implications [185]. For these reasons, the demands for developing an optimised wheelset maintenance system are growing.

As introduced in section 2.1, the most common rolling stock maintenance activity is periodic maintenance. Within this category, the major maintenance activities in a depot comprise periodic inspection, condition monitoring, routine maintenance and overhaul. This chapter presents two wheelset maintenance case studies to demonstrate the application of the railway maintenance function allocation framework. The first case study continues the wheelset inspection analysis in Chapter 5, a KUKA robotic arm was chosen as a typical RAS example. The second case study considers wheelset profiling, a wheel lathe system in depot was analysed.

6.1 Automatic robotic wheelset inspection cell case study

As railway maintenance environments are semi-structured, maintenance tasks are generally different to those for industrial robots. However, railway maintenance still contains manipulation tasks similar to those done by industrial robots, such as handling, moving and assembling tasks in depots. In addition, technologies are well established after decades, with industrial robotics first developed in 1962 [186]. An industrial robot is capable of operating with a high degree of reliability and safety and a relatively high degree of accuracy. Furthermore, industrial robots are able to adjust to many applications by having multiple sizes, a range of payload capacities and end-of-arm tooling selection. These characteristics make an industrial arm desirable for the investigation of automatic wheelset inspection. Hence, the first case study uses a KUKA industrial robotic arm as the automatic solution for wheelset function allocation. Consequently, wheelset tasks are either allocated to a human, KUKA robotic arm or both.

This case study discusses the technical feasibility, system performance and cost analysis of the preliminary design for the robotic wheelset inspection system. Finally, the LOAs of wheelset inspection system is determined based on the proposed allocation framework.

The scope of this case study is off-vehicle wheelset inspection, which normally takes place when a train requires a complete overhaul or has been involved in a major incident, e.g., derailment, where wheelsets must be disassembled and given a thorough examination such as moving the sensing heads over the wheelset and making decision based on the data.

Continuing with the wheelset inspection example in Chapter 5, wheelset inspection has been further decomposed into Set-up, Present, Search, Decide and Respond phases. According to the observations made during maintenance depot visits by the author, there exists support equipment to help the Present and Set-up stages, such as crane equipment, rotators, wheel drops and automated handling. However, Search and Decide activities are mostly performed manually, as shown in Figure 6.1.

Figure 6.1 Wheelset defects search

Also, due to the poor mobility of robotic arms, it would not be physically feasible for a single robotic arm to implement all these tasks including disassembling wheelsets from trains, cleaning and searching to identify any problems, and repairs. Furthermore, as stated in section 5.2.2, “search” and “decide” functions have a significant impact on the overall inspection quality. Above all, this case study will only focus on wheelset Search and Decide. Refer to the updated Fitts list, the preliminary allocations of Search and Decide derived from section 5.1.2 are listed in Table 6-1. It is the first analysis stage in the framework before the iterative process.

Table 6-1 Preliminary function allocation of Search and Decide

Function	Tasks	Related human/machine capabilities listed in updated Fitts list	Preliminary allocation
Search	Inspect the wheelset components to identify any problems (such as cracks, defects, corrosion, loose parts) and record any abnormality.	Ability to detect a small amount of visual or acoustic energy (**Machine)** Ability to perform repetitive routine tasks (**Machine**) Ability to reason inductively (**Human**)	Both machine and human involved
Decide	Following the inspection results, decide whether the severity level of failures exceeds the tolerance of related maintenance specifications. Then determine whether the components need further detailed NDI, or to be repaired or discarded.	Ability to reason inductively (**Human**) Ability to exercise judgement (**Human**) Ability to reason deductively, including computational ability **(Machine)**	Both machine and human involved

Based on the outcome of the preliminary allocation, both ‘search’ and ‘decide’ functions would get benefits from applying automation solutions. For example, allocating the search function to a machine frees humans from repetitive tasks. This case study will further evaluate the feasibility, system performance and cost for both tasks through the iterative process of the framework as illustrated in Chapter 5. The LOAs of the final system will be determined accordingly.

6.1.1 Robotic feasibility analysis

As shown in Figure 5.1, feasibility analysis is the first phase of the iterative process in the function allocation framework. Search as a function contains general visual inspection and NDI. Both physical and cognitive activities are involved to analyse the feasibility of the search function, while decision is a pure cognitive function. Therefore, physical feasibility will only be considered for the search function while the cognitive feasibility will be investigated for both functions. The corresponding task will be reallocated as manual if the analysis marks it to be infeasible. If the analysis shows that it is not feasible, the corresponding task will be reallocated as a manual task.

Physical feasibility

Section 4.2.1 introduced the notion that to decompose motions and assess the physical applicability of robotics, virtual 3D environments (off-line programming) would be of great help. The author has built a virtual robotic system model using a 3D simulation software environment. It is a standard package from KUKA that enables designers to visualise and to examine moving trajectories using an animated 3D model of the robotic arm and its surrounding environment. Figure 6.2 shows the complete animated 3D prototype, including models of the enclosure, robotic arm, positioner, wheelsets and wheel stand. It constructs the robotic arm and all the wheelset components based on real-world dimensions.

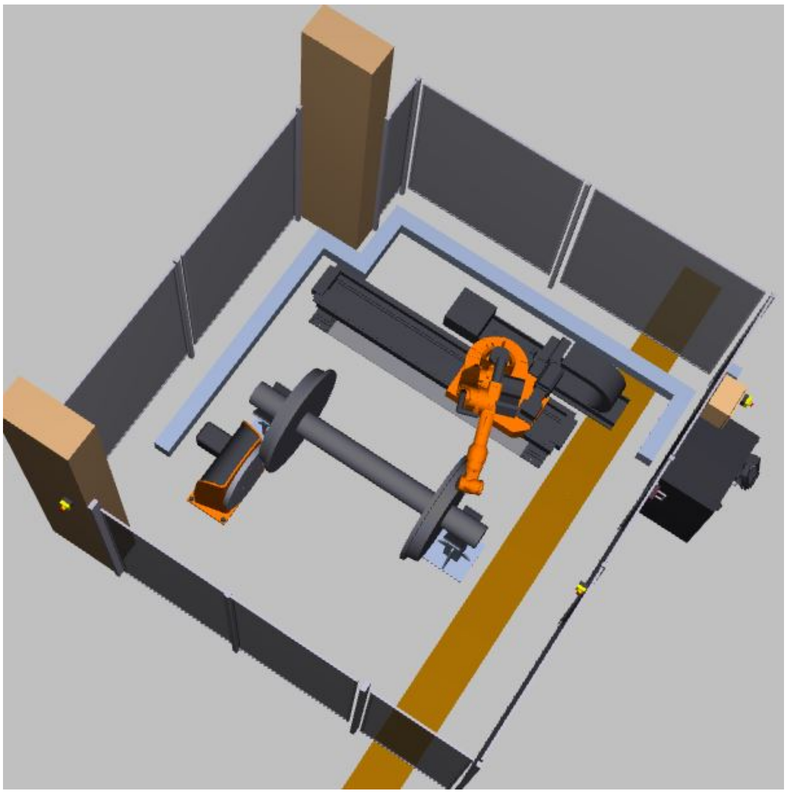


Figure 6.2 Robotic 3D animated simulation model

From the 3D virtual representation, the author has designed and verified various robot trajectories by selecting basic motions such as a linear move, a small arc of a curved path, and a small angle of orientation. Different robot parameters such as speeds and payload are also set to test. In the simulation, the robot head moves along axles and around the flange to scan and follow the surface profile. Figure 6.3(left) presents a panoramic view of the robotic cell, and Figure 6.3 (right) provides a closer view during trajectory simulation.

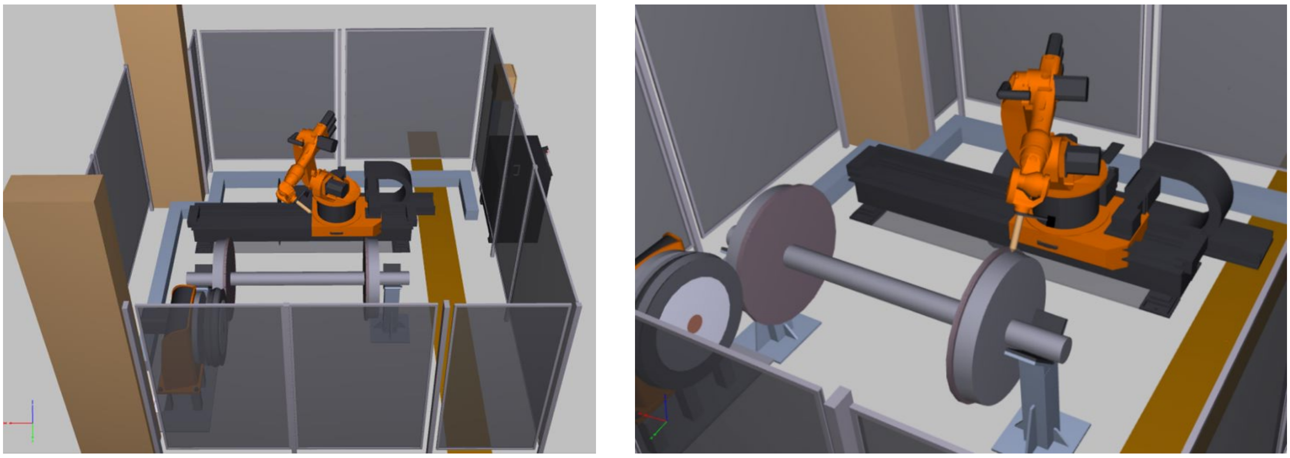


Figure 6.1 Robotic simulation

It demonstrates the physical applicability of the robotic facility which could provide full coverage of the motions for wheelset inspection.

Cognitive feasibility

A semi-structured environment in railway maintenance is defined as 'Surroundings are known, but with unidentified variations and uncertainties. Operations require the combination of known environment information and real-time sensing information'. In this case, although assuming that the wheelset has been presented in front of the robotic arm, there are still uncertainties in terms of the accurate relative locations of the wheelset and robotic arm, the precise geometry of used/worn wheelsets, and the diverse visual precision requirements. Therefore, environment navigation is a critical part of the cognitive feasibility analysis. To cope with the semi-structured environment, the author and BCRRE have proposed a multi-phase approach as follows.

- The Microsoft Kinect sensor is selected as the environment navigation tool and is applied to capture depth information

The Kinect sensor is a relatively low-cost depth sensor but is capable of producing images of decent quality which makes it widely used for robotic applications [187],[188]. As shown in Figure 6.4, the Kinect sensor can be attached onto the KUKA robotic arm to perform two static captures on both sides of the wheelset. Since the measurement distance of Kinect ranges from 0.5 to 1.2 m, the Kinect sensor can maintain a safe distance from the wheelset to avoid any potential collision.

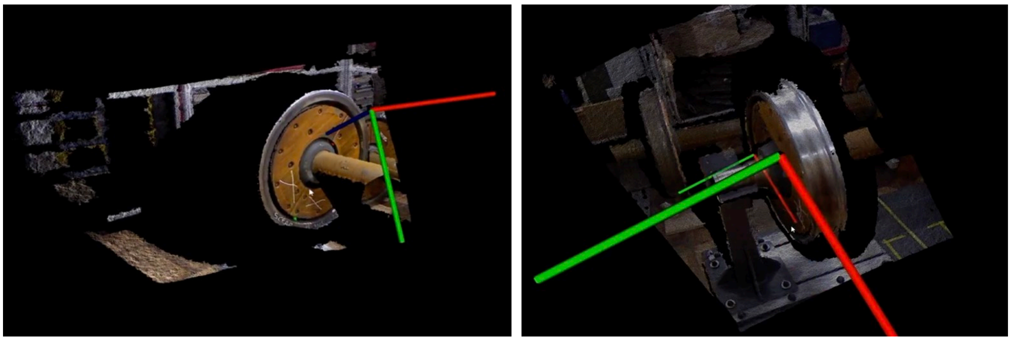


Figure 6.2 Kinect sensor information capture

- Data registration and 3D model representation

The next step is data registration, followed by pre-processing; the point clouds from different views are combined to build up a complete 3D model representation of the wheelset.

The aim of environment navigation is to navigate the location and shape of the wheelsets to further assist in visual inspection path planning. The model generates a rough shape of the wheelset and determines the relative position of the wheelset components as shown in Figure 6.5. It significantly reduces the uncertainties of the semi-structured environment. The wheelset inspection environment can be regarded as a structured environment after environment navigation.

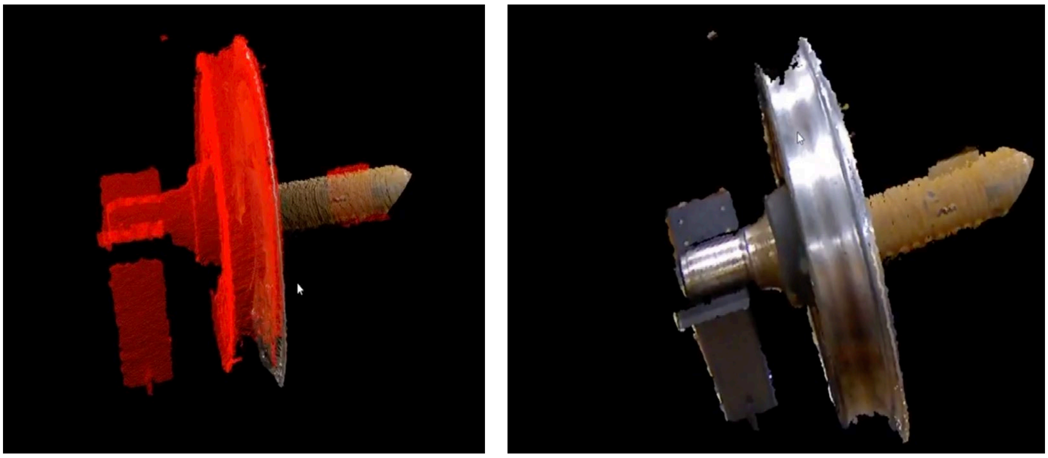


Figure 6.3 Data registration and 3D model representation

- Path planning

As shown in Figure 6.6, to verify the environment navigation results, two random points on the model are selected; the path planning algorithm can generate a designed path (sinusoidal, linear, etc.) across the surface between the two points, maintaining a constant distance.

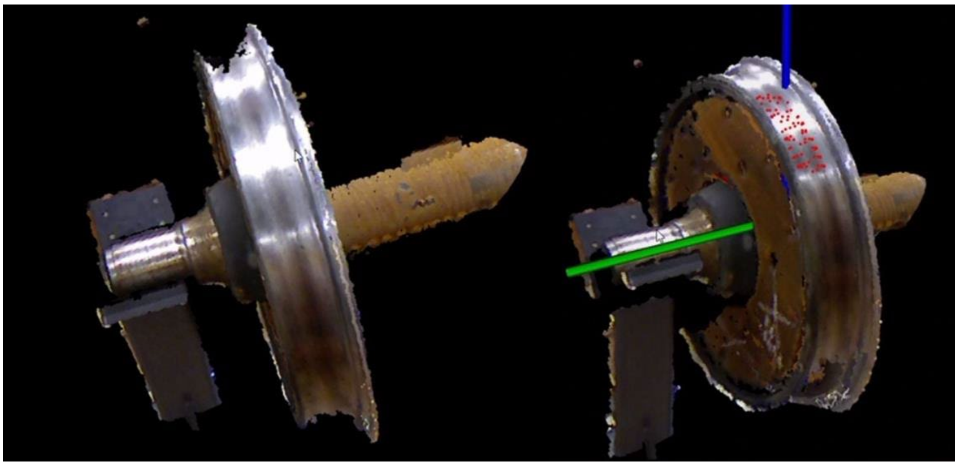


Figure 6.4 Path planning

- Path testing

The generated path can be tested by feeding the trajectory data into the 3D simulation model before operating the actual robotic arm to ensure there is no collision between the wheelset and sensing heads. Also, the tested program can be transferred directly to a real robot.

Despite the robot needing to operate in a semi-structured environment while carrying out wheelset visual inspection, it can be tested whether by applying the multi-phase environment navigation approach, the robotic arm would be capable of coping with uncertainties during visual search.

Once the point clouds of wheelsets have been obtained, ideally, they can be used for more refined NDI path planning. However, some experimental results show that the random error of Kinect sensor depth measurement can range from a few millimetres to about 4 cm [189]. Besides that, there can be random errors in the process of robotic end-of-arm tooling calibration. Given that certain NDI technologies require the surface geometry to be known with a high degree of accuracy (< 2 mm) [190][41], the accuracy of the Kinect sensor is not good enough to support more refined NDI search path planning, and there would be a risk of contact between the wheelset and NDI probes.

Although there exist automated NDI examples in the rail industry (as stated in Section 2.5), in the present case study, it is infeasible to automate the NDI search function and it would be allocated to humans.

Therefore, the visual search task becomes both physically and cognitively feasible, while the NDI search is physically feasible but cognitively infeasible.

Following the inspection results, the Decide task is carried out to decide whether the severity level of failures exceeds the tolerance of related maintenance specifications. Then, determination is made whether the components need to be repaired, discarded or released to service. Despite the developments of artificial intelligence, automated decisions still have not been fulfilled. There are few research publications on automated railway maintenance decisions. Winter and Dodou [26] pointed out that even in highly automated systems, humans still retain the role of making high-level decisions. Therefore, the decision will be allocated to humans.

Table 6-2 shows the updated allocation results after the first iterative stage (feasibility analysis) of the function allocation framework.

Table 6-2 Allocation decision after feasibility analysis

Function	**Allocation decision**
Visual search	Feasible for automation
NDI search	Human
Decide	Human

Based on the feasibility analysis results, only visual search is proved to be feasible and it will be further evaluated under the guidance of the framework. NDI search and decision are terminated in the iterative process. As a result, they are labelled as operating manually.

6.1.2 Human and robotic system performance analysis

The automatic robotic inspection cell aims to achieve an improved overall system performance to replace humans. In this evaluation phase, human performance and robotic system performance will be discussed comparatively. The objective is to prove the benefit of allocating the visual search to robotics.

Section 4.3.1 selected RAMS as the performance criteria for a railway maintenance system. As the four criteria do not influence the overall system performance equally, there is a need to determine the relative level of importance for each criterion.

AHP survey

As a similar process as illustrated in section 3.3, AHP is adopted to derive the RAMS weights. AHP pairwise information was gathered from experts through a questionnaire during industry panel discussions. There were four panellists, two of whom are rail industry academics. One panellist is a former rail rolling stock maintainer, and the other is a former RSSB research manager. In the questionnaire, experts compared RAMS criteria against each another (Table 6-3). Same as the example in section 3.3, the importance level is divided into five scales: equal, marginally strong, strong, very strong and extremely strong corresponding to number 1,3,5,7,9.

Table 6-3 RAMS questionnaire

Criterion 1	**Criterion 2**	**Most Important**	**Intensity**
Reliability	Availability		
Reliability	Maintainability		
Reliability	Safety		
Availability	Maintainability		
Availability	Safety		
Maintainability	Safety		

Questionnaire results were collected as shown in Table 6-4.

Table 6-4 Questionnaire results

Criterion 1	**Criterion 2**	**Which criterion is more important?**	**Intensity**
Reliability	Availability	Availability	3
Reliability	Maintainability	-	1
Reliability	Safety	Safety	7

Availability	Maintainability	-	1
Availability	Safety	Safety	5
Maintainability	Safety	Safety	7

The questionnaire results can be re-expressed as Table 6-5:

Table 6-5 Importance level against each other

Criterion	Reliability	Availability	Maintainability	Safety
Reliability	1.000	0.333	1.000	0.143
Availability	3.000	1.000	1.000	0.200
Maintainability	1.000	1.000	1.000	0.143
Safety	7.000	5.000	7.000	1.000

Then a matrix can be derived as:

$$A = \begin{matrix} 1.000 & 0.333 & 1.000 & 0.143 \\ 3.000 & 1.000 & 1.000 & 0.200 \\ 1.000 & 1.000 & 1.000 & 0.143 \\ 7.000 & 5.000 & 7.000 & 1.000 \end{matrix} \tag{6.1}$$

Finally, the eigenvector of matrix A is calculated to derive the relative ranking of criteria:

$$Eigenvector = \begin{bmatrix} 0.080 \\ 0.154 \\ 0.105 \\ 0.661 \end{bmatrix} \tag{6.2}$$

The eigenvector values indicate the priorities of RAMS respectively. By assigning the priority values to RAMS, the overall system performance analysis can be derived as shown in Figure 6.7.

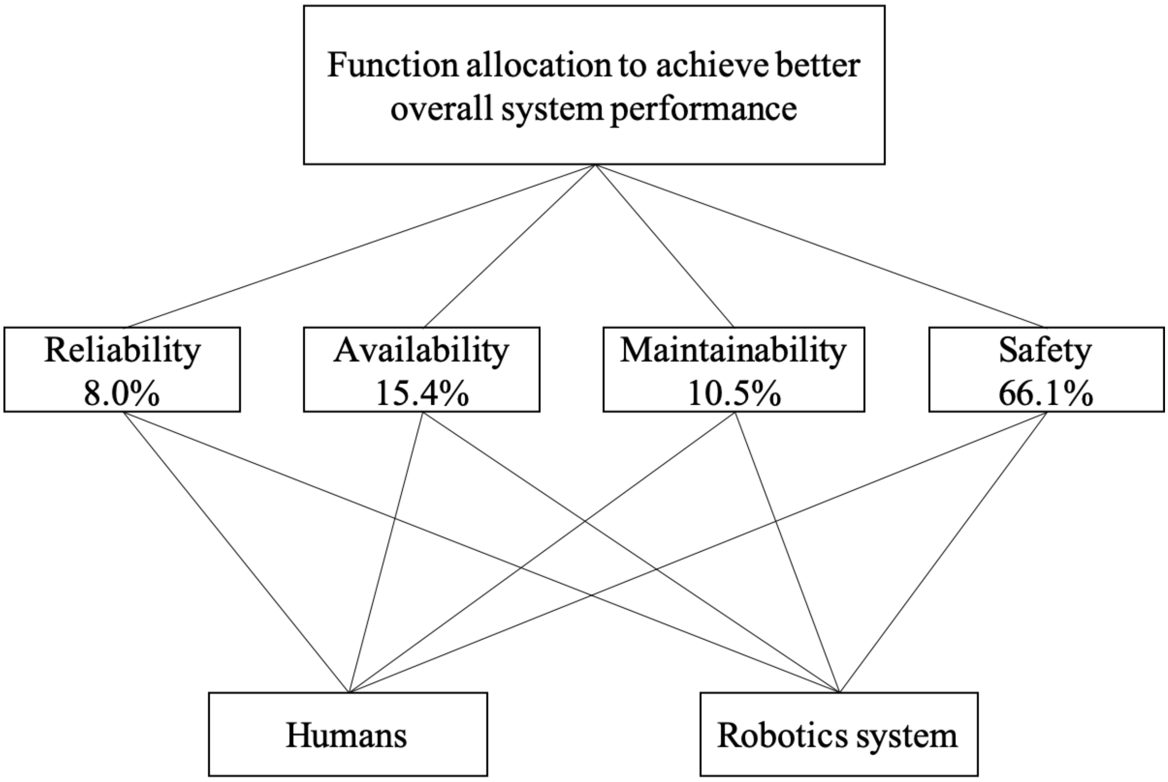


Figure 6.5 RAMS criteria weights

It can be seen from the AHP analysis results that among those four criteria, safety dominates the overall system performance.

In section 4.3.1, it was stated that RAM can be grouped and considered together and suggested that safety is evaluated separately. Also, assessing RAM is strongly based on failure analysis. Therefore, human errors and robotic failures will be discussed first in the following section. Since FTA is applicable for both RAM and safety analysis as reviewed, FTA will also be constructed.

Human error in wheelset visual inspection

A human error is generally defined as the failure to perform a task which may lead to interruption of scheduled routine, asset damage or failure to meet task requirements [158]. It is either an unintended action or a decision error. In the rail industry, identifying and quantifying human errors are key steps to assess human reliability and safety [163]. Human error quantification techniques are based on probability. To provide generic estimates of human error probability in this wheelset inspection scenario, the Railway Action Reliability Assessment (RARA) method proposed by the RSSB is applied [191]. RARA is a quantification technique for assessing the likelihood of human error in railway tasks which can be used as an aid in making safe decisions and RAM analysis.

The steps of applying RARA are as follows.

1. Identify the task which requires estimation of the human error probability;
2. Select the Generic Task Type (GTT) from Table 6.6 which best matches the task;
3. Select any Error-Producing Conditions (EPCs) from Appendix A which are relevant to the task being assessed;
4. Review the selections of GTT and EPCs to see if there are any overlaps between GTT and EPCs; if any, modify accordingly;
5. For each selected EPC, estimate the assessed proportion of effect for the EPC, which will be a value between 0.1 (a small effect) and 1 (full effect). Then, calculate the final effect using the formula:

$$Effect\ (A) = (MA - 1)\ \times\ APOA\ + 1 \tag{6.3}$$

where MA = the maximum effect associated with an EPC from Appendix A; AOPA = assessed proportion of effect value between 0.1 and 1 selected by the analyst, where 0.1 is a small effect and 1 is the full effect.

6. Finally, the human error probability can be calculated with the formula

$$Human\ Error\ Probability\ (HEP) =\ GTT\ \times\ A_1 \times A_2 \ldots \times A_n \tag{6.4}$$

where GTT = the HEP associated with a GTT; A = effect for each EPC calculated in step 5.

7. Then review the calculated HEP against other available estimation data to decide if the estimation results make sense.

There are two key elements when applying RARA: GTT and EPC. As shown in Table 6-6, GTT consists of eight task types; it divides human performance into three categories which are Skill, Rule and Knowledge-Based (S-R-K). GTT aims to provide a comprehensive coverage of human performance to aid estimation of HEP.

For example, during a visual inspection search task, the inspector firstly moves their eyes or uses visual aid tools to judge the condition of the item and make a quick judgement on whether there is a fault or not. The description consists of the following human actions:

'Move eyes or use visual aid tools to judge the condition' is a skill-based task. Referring to the GTT lists, R4: 'a skill-based task (manual, visual or communication) when there is some opportunity for confusion' would best match the visual search, and the HEP would be 0.003.

Table 6-6 Generic task types[191]

	GTT	HEP	Bounds
More automated and skill-based processes	R1. A correct response to a system command even when there is an automated system providing accurate interpretation of the system state.	0.00002	0.000006–0.0009
	R2. A completely familiar, well-designed, highly practised task which is routine.	0.0004	0.00008–0.007
	R3. A simple response to a dedicated alarm and execution of actions covered in procedures.	0.0004	0.00008–0.007
	R4. A skill-based task (manual, visual or communication) when there is a chance for confusion.	0.003	0.002–0.004
	R5. A fairly simple task performed rapidly or given insufficient or adequate attention.	0.09	0.06–0.13
More effortful and rule-based processes	R6. Restore or shift a system to an original or new state, following procedures with checking.	0.003	0.0008–0.007
	R7. Identification of situation requiring interpretation of alarm/indication patterns.	0.07	0.02–0.17
Thinking outside procedures and knowledge-based processes	R8. A complex task requiring a high level of understating and skill.	0.16	0.12–0.28

EPCs are issues that are regarded as having negative impacts on human performance and they are used to adjust the GTTs to be closer to real-world tasks. EPCs would increase the HEP associated with GTTs. All EPCs are listed in Appendix A.

For example, the RSSB human factors team [191] indicates that performing inspection tasks requires all aspects of training. Even a senior inspector will meet a fault that has never been experienced before. The display screen may present very noisy signals which makes identification of faults difficult. Also, there is no recovery opportunity for a missing fault. So, related EPCs could be:

T1. 'Unfamiliarity with a situation which is potentially important, but which only occurs infrequently, or which is novel.'

As stated in section 4.3.2, FTA may be used for both qualitative and quantitative analysis to examine the errors and failures in the system at various levels; therefore, it is applied in this example to investigate the HEP in wheelset visual inspection activities. Based on the task description and potential human errors, a fault tree was developed as shown in Figure 6.8.

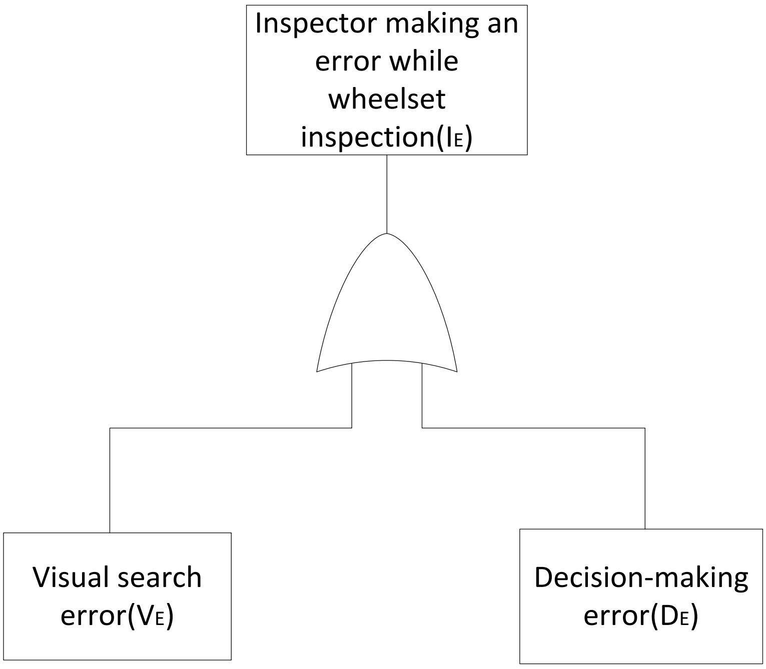


Figure 6.6 Human error FTA

In this FTA, 'Inspector making an error during wheelset visual inspection tasks' was defined as a top event. The top event was split into two aspects of human errors, visual search and decision-making. The probability of occurrence of the top event $P(x0)$ is given by the formula:

$$P(x0) = 1 - \{\prod_{i=1}^{n}\{1 - P(xi)\} \quad (6.5)$$

where $P(xi)$ is the occurrence probability of OR gate input event xi; for $i = 1, 2, 3 \ldots, n.$

In this case, $P(x0)$ is the probability of inspection error, $i = 2.$

Referring to similar scenarios listed in the RARA manual [191], the author estimated the visual inspection error and decision-making errors respectively.

1. Visual search error

GTT selected is R4: 'A skill-based task (manual, visual or communication) when there is some opportunity for confusion' = 0.0003

EPC selection 1: C 'Operator inexperience' = 3

EPC selection 2: P2 ‘Fatigue from shift and work pattern’ = 2.6

Both APOA = 1

EPC 1 Effect = $(3 - 1) \times 1 + 1 = 3$

EPC 2 Effect = $(2.6 - 1) \times 1 + 1 = 2.6$

$$\mathrm{HEP} = 0.0003 \times 3 \times 2.6 = 0.002 \tag{6.6}$$

2. Decision-making error

GTT selected is R7: ‘Identification of situation requiring interpretation of alarm/indication patterns’ = 0.07

EPC selection 1: T1 ‘Unfamiliarity with a situation which is potentially important, but which only occurs infrequently, or which is novel’ = 17

APOA = 0.5

EPC 1 Effect = $(17 - 1) \times 0.2 + 1 = 4.2$

$$\mathrm{HEP} = 0.07 \times 4.2 = 0.294 \tag{6.7}$$

Based on the fault tree analysis and equation (5), the probability of human failure during inspection is calculated as:

$$\text{Human failure probability } = 1 - [(1 - 0.002) \times (1 - 0.294)] = 0.295 \tag{6.8}$$

The analysis shows that the failure probability of a human visual inspection system is estimated as 0.295.

Robotic system failures

A comprehensive FTA for the KUKA robotic inspection system has been designed and is presented in Figure 6.9. The fault tree takes the KUKA robot structure as the template; however, the FTA is also applicable to other robot types. The automatic inspection system under consideration consists of a communication system, software command console, environment navigation system, end-of-effector tooling system, safety system, batteries, brake system, operating system, driver system and manual buttons. To assess the robotic system's reliability, the following assumptions are associated with this FTA analysis:

1. All components failure rates are constant
2. All failure modes are independent
3. The automatic inspection system is composed of a robot and peripheral system
4. The automatic inspection system fails when the robot fails

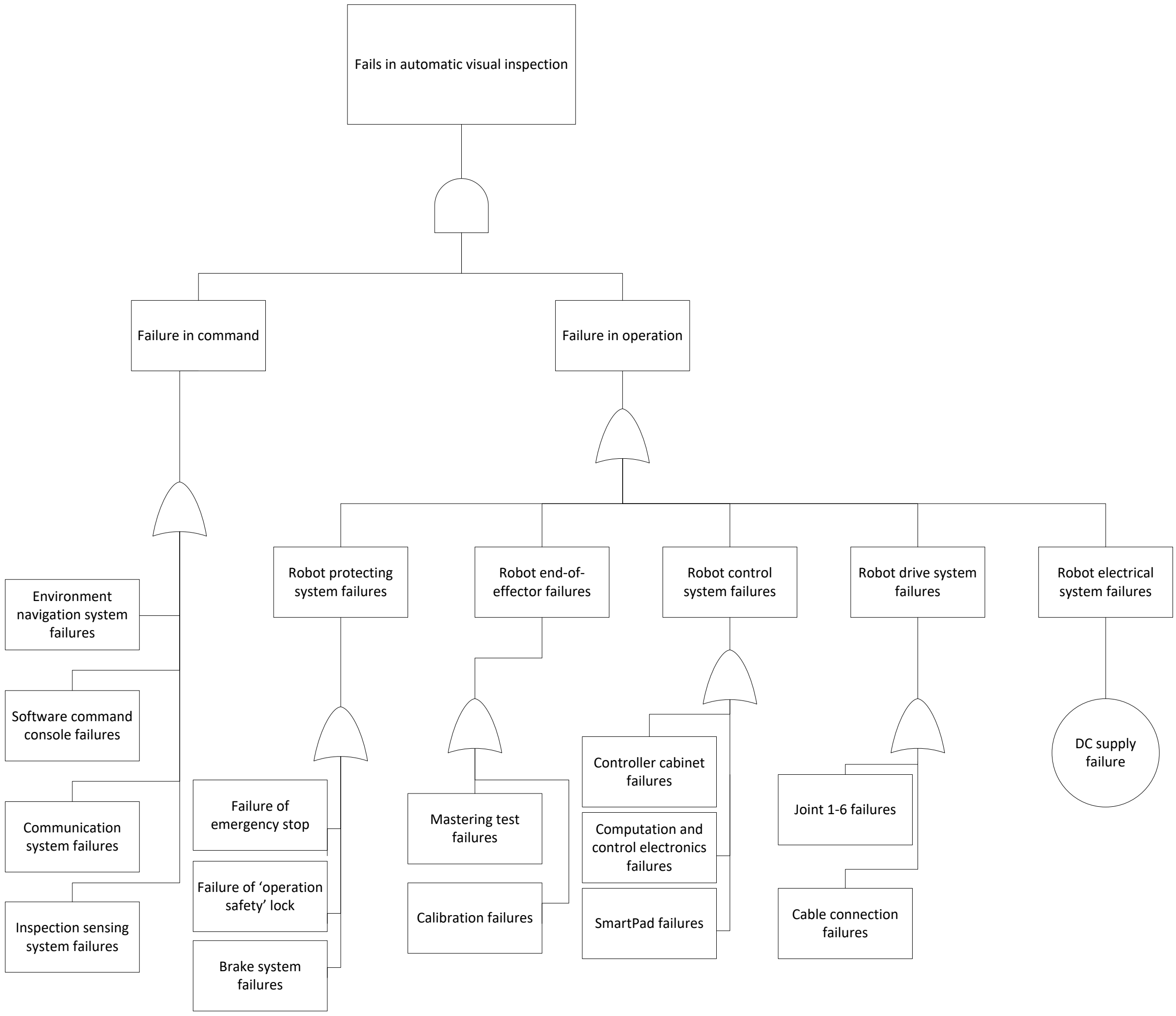


Figure 6.7 KUKA robotic failure FTA

One of the methods for estimating the failure probability of the KUKA robotic system is to quantify the FTA in Figure 6.9, similar to the human error assessment, by applying the same formula as equation 6.5. However, this method for assessing RAM is not accurate or necessary as RAM parameters (MTTF, MTBF and MTTR) can be covered sufficiently by historical evidence of robotic applications. In addition, these statistical values could easily be found in published KUKA documentation or academic literature. Hence, Figure 6.9 only provides qualitative FTA analysis. Table 6-7 shows the statistical information for KUKA RAM [192] which indicates that the failure rate is much less than the HEP.

Table 6-7 KUKA RAM parameters [192]

Factor	Hardware	Software
MTBF (hours)	79696	106261
MTTR (hours)	0.51	0.39
Failure rate	0.00001255	0.000009411

Reliability, availability and maintainability all describe the probability of an item performing a certain action within a given time interval. Considered from the perspective of quantitative analysis, robotic reliability is quantified as MTBF, maintainability is quantified by MTTR, and availability can be written as MTBF/(MTBF + MTTR) [150].

It can be seen that robotic systems would significantly improve RAM performance for the wheelset visual inspection.

Safety analysis

In terms of system safety analysis, the RSSB documents: Guidance on the Common Safety Method for Risk Evaluation and Assessment[163] recommended that existing system safety measure and newly system safety identification can be achieved by recording the potential hazards and then list the safety requirements. For robotics system , Dhillon[193] summarised there are three lofty design laws as follows.

(1) A robot must not harm a human being, nor through inaction allow one to come to harm.

(2) A robot must always obey human beings, unless that is in conflict with the first law.

(3) A robot must protect itself from harm, unless that is in conflict with the first or second law.

“Not to harm a human being” is always the highest priority for robotic operations. Safety is defined as the freedom from unacceptable risk from harm.

To help avoid any hazards to ensure safety, the author has considered the standard operating procedures (SOPs) as well as risk assessments when people operating robotics. As part of risk assessment, the potential hazards and solutions guides are listed in Table 6-8. Operation hazards would be eliminated with obeying the SOP and solutions guide. It is noteworthy that robotics is located inside an aluminium cage covered by Perspex windows, humans are banned from the operation area beyond the maximum reach of robotic arm therefore hazards are theoretically eliminated by avoiding the direct contacts with humans. In summary, applying automation would help eliminate potential hazards, the safety performance would be improved. It can be concluded from this section that robotic system would help to improve both RAM and safety performance, therefore, visual search task is assigned to the robot.

Table 6-8 KUKA robotic risk assessment

Potential Hazards of Robotic inspection system	**Solutions Guide**
Trip hazard inside the robot cell	Be cautious about uneven floor and metal objects inside the robot cell. Safety boots must be worn.
Hazard of abnormalities or unexpected movements when doing the calibration work and mounting end effectors to the tip of the robotic arm	Operators must hold the smartpad. The robot must be operated when there is a member of staff present in the lab in the case of a hazardous event. in the case of hazardous event, either of the emergency buttons (wall mounted/ smartpad mounted) must be pressed to stop the robot from moving.
Hazard of hitting by robot arm when operating in T1 mode (< 250 mm/s)	Safety distance (0.5 m) from robot should be kept. The robot must be only be operated when there is a member of staff present in the lab.
Hazard of collision when operating in T2/Auto/External modes	Programs must be tested in T1 mode first. No-one is allowed to be inside the robotic cell when running programs in these modes. All the cell doors must remain locked shut while the robot is being operated. The robot is equipped with force detection sensor to minimise damage in the event of collision.
High voltage: Hazard of electrical shock	The door of the controller cabinet must be shut at all times. The controller must be switched off before any attempt to open the controller cabinet door is made.
Hazard of abnormalities or unexpected movements when mounting end effector to the tip of the robotic arm	The controller must be switched off when mounting/discounting tool on/off the robot end-effector.

Table 6-9 shows the allocation results after the second process in the framework

Table 6-9 Allocation decision after system performance analysis

Function	Allocation decision
Visual search	Potential to improve system performance if allocate to RAS
NDI search	Human
Decide	Human

6.1.3 Robotic cost analysis

Referring to the economic analysis of other robotic applications [194],[195], documents published by the robotic companies [170],[196], and sales brochures, the author has summarised the life cycle costs of a robotic inspection cell as follows. The robotic arm is a mid-scale product thus its life cycle cost fits the distribution of the existing medium-sized product.

1. Cost of purchasing a robot.

2. Robot installation costs, including the cost of labour and materials, flooring and foundation preparation, facilities and interface equipment between robots and fixtures.

3. Rearrangement costs – installation of fences, conveyors, etc.

4. Project management cost – including feasibility study, commissioning, etc.

5. End-of-arm tooling costs – including the cost of calibration tools (positioners), end effectors, special sensors due to different robot applications, etc.

6. Direct labour cost – the operation of a robot cell.

7. Cost of staff training.

8. Start-up costs – work delayed because of installation.

9. Indirect labour cost – repair and maintenance of the robotic system.

Items 1 to 5 listed above are investment (fixed) costs, and 5 to 8 are operating (variable) costs. Generally, the total cost of a specific system is calculated by summing up all the cost elements. The initial expenditure and training costs for this case have been produced:

Table 6-10 Robotic system cost[194],[195] [170],[196]

Fixed costs of robotic system	
Item	**Cost**
Purchasing the robotic arm and installation	£150,000.00
Kinect sensor	£120.00
Simulation software	£10,000.00
Staff training	£8,000.00
Total	£168,120.00

A report from the robot company pointed out that the total fixed cost of a robotic application varies between £150k and £600k. Ongoing robotic maintenance costs vary between £500 and £3000 per year [170]. The operational life of a robotic arm is typically between 7 and 8 years. However, the analysis using the framework above shows that the robotic arm is only better at performing the visual search part of the wheelset inspection. Humans are still required to manually complete the inspection or assist the robot with other functions. Therefore, the use of robotic arms does not significantly reduce the labour costs of wheelset inspectors but rather increases the labour costs required to maintain and operate the robots. Since it is only feasible to automate one function (visual search) at this stage, it is not worth automating at this stage from an investment point of view, even if robotics could bring small benefits in terms of improved visual search performance.

Table 6-11shows the allocation results after the third process in the framework.

Table 6-11 Allocation decision after cost analysis

Function	Allocation decision
Visual search	Human
NDI search	Human
Decide	Human

It can be seen that no single function can fully pass all the evaluation stages (technical feasibility, system performance and cost). Therefore, wheelset inspection is allocated as non-automatic.

6.2 Automatic wheel lathe case study

Based on wheelset inspection results, operators can decide whether the wheelsets are to be released for service, sent back to the depot for reprofiling or abandoned, as shown in Figure 6.10. Due to the wear that occurs during the operation, wheelsets may have various defects, leading to unacceptable wheel condition. Among those, certain defects, such as out of roundness wheels, wheel flats and flange wear, can be maintained by wheelset reprofiling [197]. This case study discusses the wheelset reprofiling situation.

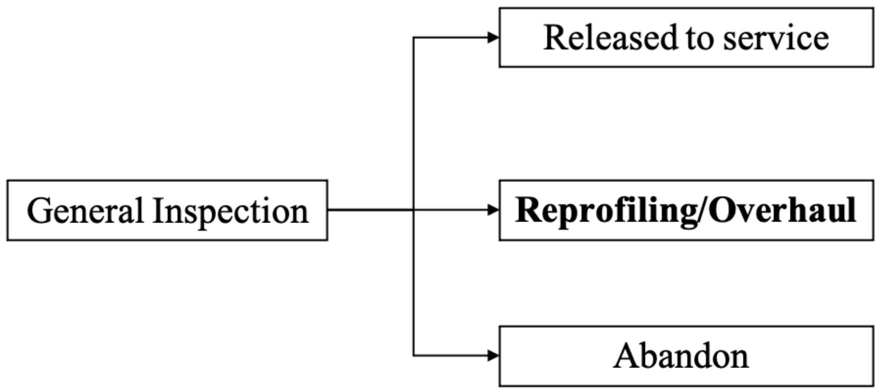


Figure 6.3 Activities after general inspection

Different from the robotic inspection case study presented above, this case study was not conducted in the laboratory. The information used for framework analysis was gathered mainly from the author's visits, observations and conversations with experts working in a depot.

To investigate a typical wheelset reprofiling system in a UK depot, the author visited Temple Mills Depot. It is a site covering all servicing, heavy maintenance and repair work of Eurostar trains. The site includes a dedicated wheel lathe facility for wheel reprofiling, as shown in Figure 6.11.

Figure 6.4 Wheel lathe in Temple Mills Depot

This type of lathe is a computer numerical control (CNC) machine used to turn wheelsets in situ on the train. As railway wheels are turned, the tread profile is restored, and wear and defects are also removed, while a certain amount of the wheel diameter and full flange thickness of the wheel is lost [198]. The wheel lathe system in Temple Mills Depot involves both human and machine activities and so can be regarded as a semi-automatic system.

Based on observation, the detailed task description, task analysis and preliminary function allocation are presented in Table 6-12. The general task description starts when the trains arrive in the correct profiling area. Firstly, the parameters of the wheelset are measured, and the amount needing to be cut away is calculated. Then the lathe gets to work to cut the wheels.

Once the cutting is done, the wheels are measured again. If the reprofiled wheelset complies with the standards, the train will be put back into service.

Table 6-12 Wheel lathe preliminary function allocation

Function	**Tasks**	**Related human/machine capabilities listed in Fitts**	**Preliminary allocation**
Positioning	Move the train to the correct machining area.	Ability to perform repetitive routine tasks **(Machine)** Apply great force smoothly and precisely **(Machine)**	Machine
Pre-measurement	Wheelset parameters are measured which includes wheelset back-to-back distance, flange height/thickness/inclination and wheel diameters, etc. Then the wheel is rotated very slowly to measure the wheel diameters and decide whether the wheel is out of round.	Ability to perform repetitive routine tasks **(Machine)**	Machine

Calculation	Based on the measurement results, calculate how much to cut off. The machine can indicate the number, but this step normally relies on properly trained people to decide what they want the machine to do.	Ability to reason inductively **(Human)** Ability to reason deductively, including computational ability **(Machine)**	Both human and machine involved
Machining	Lathe cuts off the wheel.	Ability to perform repetitive routine tasks **(Machine)**	Machine
Re-measurement	Same process as 'Pre-measurement'.	Ability to perform repetitive routine tasks **(Machine)**	Machine
Decision	The operators check whether the reprofiled wheelset meets the standards and decide whether it can be released into service.	Ability to reason inductively **(Human)** Ability to exercise judgement **(Human)**	Human

6.2.1 Wheel lathe feasibility analysis

As semi-automatic/automatic wheel lathe systems already exist in a realistic maintenance environment, the feasibility of automation has already been proven to be applicable in the depot. Table 6-13shows the feasibility analysis results for the automation of wheel profiling functions. It is worth noting that due to the lack of physical capability of humans (e.g., comparatively weak power output), in this case, positioning and machining are considered only able to be done by wheel lathe system. Thus, those two functions are allocated to the machine. The next evaluation phase (performance analysis) will only consider measurement and calculation functions.

Table 6-13 Feasibility analysis

Function	Feasibility analysis
Positioning	Only machine is feasible
Pre-measurement	Both human and machine are feasible
Calculation	Both human and machine are feasible
Machining	Only machine is feasible
Re-measurement	Both human and machine are feasible

6.2.2 Human/wheel lathe system performance analysis

Based on observations at Temple Mills Depot and conversations with the operators, for wheelset reprofiling, the performance analysis is mainly focused on the reliability and safety between humans and the automatic wheel lathe system. For the safety analysis, since there is no physical risk to the calculation function, only the physical risk to the measurement function is considered. However, reliability requires the analysis of both the measurement function and the calculation function, so this section will analyse the reliability and safety of the measurement function as well as the reliability of the calculation function.

Measurement/re-measurement

The present case study applies the same RARA method as in the robotic inspection case study to analyse the probability of human error in the measurement function. The fault tree analysis is presented in Figure 6.12.

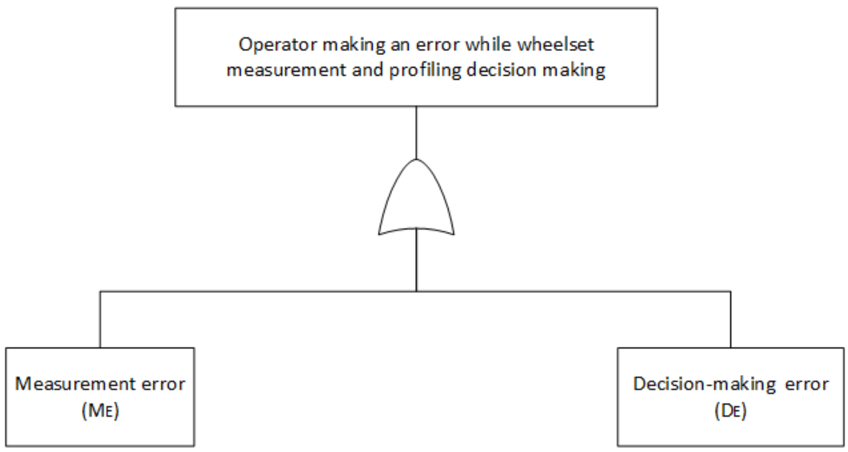


Figure 6.5 Fault tree analysis

1. Measurement error

GTT selected is R6: 'Restore or shift a system to an original or new state, following procedures with some checking.' = 0.003

EPC selection 1: P2 ‘Fatigue from shift and work patterns’ = 2.6

APOA = 0.5

EPC 1 effect = (2.6 − 1) × 0.5 + 1 = 1.8

$$\text{HEP} = 0.003 \times 1.8 = 0.0054 \quad (6)$$

2. Decision-making error

GTT selected is R8: ‘A complex task requiring a high level of understanding and skill’ = 0.16

EPC selection 1: C ‘Operator inexperience’ = 3

APOA = 1

EPC 1 effect = (3 − 1) × 1 + 1 = 3

$$\text{HEP} = 0.16 \times 3 = 0.48 \quad (7)$$

Based on the fault tree analysis and equation (5), the probability of human failure during inspection is calculated as:

$\text{Human failure probability} = 1 - [(1 - 0.0054) \times (1 - 0.48)] = 0.483$

The analysis shows that the failure probability of a human visual inspection system is estimated as 0.483.

In contrast, the wheel lathe system at Temple Mills Depot is calibrated every week to ensure the accuracy of measurement results and system reliability. A manual gauge check is applied every time before using the lathe. These theoretically ensure a high degree of accuracy and reliability of the wheel lathe system. As part of the risk assessment, the potential hazards when measuring the wheels and solutions guides are listed in Table 6-14 . Operation hazards would be avoided by obeying the solutions guide. Besides that, the depot has to ensure all operators are appropriately trained and competent before commencing work on the lathe.

Table 6-14 Potential hazards of wheel measurement/re-measurement

Potential hazards of wheel measurement/re-measurement	**Solutions guide**
Hazard of being hit by objects on the lathe, such as swarf or tools	Be cautious about uneven floor and metal objects. Safety boots must be worn. Ensure operators wear safety glasses when operating the lathe. The floor surface must not be slippery and must be kept free of loose items and swarf.
Hazard of entanglement in the moving parts on the lathe e.g., clothes, hair	Long hair and loose clothing must be secured, and dangling jewellery must not be worn when operating the machine.
Hazards of sharp edges on the cutters e.g., work pieces or swarf	Be cautious about uneven floor and metal objects. Safety boots must be worn.
Hazard of electrical shock	The operators must make sure the system is powered off when directly touching it. Ensure there are emergency stop buttons present and identifiable and can be reached by employees from all positions when operating the lathe.

It is noteworthy that when the wheel lathe is operating, humans are banned from the operation area beyond the maximum reach of the wheel lathe, therefore hazards are theoretically eliminated by avoiding direct contact with humans. In summary, applying automation would help eliminate potential hazards, and the safety performance of the measurement function would be improved.

The calculation function can be described as humans/machines calculating the size of the wheel to be cut based on the measurement results. As a CNC wheel lathe, the previous operation information is stored in the database. At the same time, there are some parameters stipulated by relevant standards as specifications. It would be easy to use the machine to calculate how much needs to be cut for profiling, to get the results then put humans in a position of greater authority. However, as the wheelset is a safety-critical component, properly trained operators are still involved in the calculation process. Maintenance engineers at depots acknowledge that while 'calculations' can be fully automated, there is still a lack of trust in the machine, as trust often dictates the use of automation [21]. With this 'human trust' issue in mind, in this case study, the calculation function would first be assigned to the machine to obtain the results and then the human placed in a more authoritative position.

Therefore, wheel measurement/re-measurement functions are suggested to be fully assigned to the machine. The calculation function would suggest allocating to machine but puts the human in a more authoritative position for review. Table 6-15 shows the allocation results after the performance evaluation process in the framework.

Table 6-15 Allocation decision after system performance evaluation

Function	**Allocation decision**
Positioning	Machine

Pre-measurement	Machine
Calculation	Machine, but human placed in a more authoritative position
Machining	Machine
Re-measurement	Machine
Decision	Human

6.2.3 Cost discussion

As stated in Section 6.2.1, due to the lack of physical capability of humans (e.g., comparatively weak power output), positioning and machining are considered only able to be done by the wheel lathe. Hence only the benefits of being able to automate measurements and being able to help calculate the parameters to be cut will be analysed.

According to a report by BBC News on April 25, 2019, a £1.6m wheel lathe is installed in ScotRail's Inverness Depot[199].

Labour costs for hiring human maintenance staff are briefly listed and calculated below. The cost estimate for an employee on a maintenance site is for a typical year, including yearly wages, cost of annual leave, cost of floor space, cost of equipment, etc.

To calculate the associated labour costs, the following assumptions are made.

- The actual cost per year is around 60k (cost calculators)
- The wheel lathe would replace five operators

Comparing the payback period or the return on investment (ROI), the payback period is the number of years it takes for a company to recover its original investment for a project. The shorter the payback period, the more the attractive the investment. The aim of cost analysis is to estimate the break-even point to evaluate the trade-off. The ROI was estimated as:

Payback period = $\frac{\text{Total investments}}{\text{Total yearly savings}} = \frac{1600k}{60\text{k}\times 5} = 5.3 \text{ years}$

The lathe in Temple Mills Depot has been used for over 10 years now; normally, a wheel lathe will be used for more than 20 years. This is obviously far beyond the calculated payback period. Furthermore, the installation of a new wheel lathe will improve the performance and reliability of services in the region which would also bring economic benefits. Hence, from an investment point of view, it is worth investing in an automated wheel lathe system. The final allocation suggestion is the same as presented in Table 6-15. Thus, the suggestion is that the whole reprofiling system is automated with a high LOA of level 5 to 6.

6.3 Conclusion

6.3.1 Evaluation process for the proposed function allocation framework

In this chapter, the author has demonstrated the evaluation process for the proposed function allocation framework using examples of wheelset inspection and wheelset profiling.

a) Task analysis and preliminary allocation

In the first case study, wheelset inspection is decomposed into visual search, NDI and decision. Mapping the inherent characteristics of these functions with an updated Fitts list suggests allocating visual inspection and NDI to RAS and decision to humans. Similarly, the second case study considered wheelset profiling; after the task analysis and the guidance of an updated Fitts list, the introduction of automation is considered for positioning, measurement, machining and calculation, while decision is allocated to humans.

b) Feasibility analysis

The KUKA robotic arm was selected as the RAS example to further investigate the function allocation of wheelset visual search and decision.

The 3D animated robotic simulation model shows that the robot is capable of performing full coverage of the inspection motions of the wheelset, which proves the physical feasibility. Then, the multi-phase approach for environment navigation evidences the capability of the robotic arm to determine the relative position of the wheelset components in the semi-structured railway maintenance environment. However, despite there being good arguments for automation of NDI and decision-making tasks these days, the technologies are not well enough developed, thus NDI and decision are allocated to a human after feasibility evaluation, and visual search tasks will be further evaluated.

As semi-automatic/automatic wheel lathe systems already exist in a realistic maintenance environment, the feasibility analysis was done based on site observations and conversations with the operators working in the depot. It is feasible nowadays to automate all the functions in the depot suggested for allocation to machines, based on the updated Fitts list. Hence the allocation decisions remain the same.

c) System performance

The secondary evaluation phase is system performance. In the first case study, the questionnaires from the railway industry/academic panellists helped to derive the RAMS weights which can be further used for evaluation of wheelset visual inspection system performance. The following RAMS analysis revealed that the KUKA robotic arm improves the overall system performance considerably compared with humans. So, visual search remains allocated to robotics at this stage. For the wheel lathe, system reliability and safety are selected as KPIs; based on the performance analysis, a modern automated wheel lathe would improve both reliability and safety, so the allocation decisions remain the same.

d) Cost analysis

Through a cost analysis, the costs and benefits of investing in the KUKA robotic system and automated wheel lathe were identified. It was ultimately decided that visual search would be non-automated and suggested that it is not worth taking robotic inspection forward to full-scale implementation in the current form. In contrast, the introduction of a wheel lathe into a depot system would bring benefits and is worth implementing.

The outputs of the framework indicated that none of the functions are allocated to the robotic inspection system. However, a high LOA (level 5 or 6) wheel lathe system is suggested.

6.3.2 Framework evaluation and discussion

Two case studies have been selected in this chapter to verify the applicability of the framework in a railway maintenance environment. The main difference between these two case studies is that robotic inspection is not yet used in industrial maintenance depots in the UK, whereas wheel lathe systems are already widely automated.

The robotic inspection case study allows for verification of the framework's applicability to concepts that have not yet been implemented at all. That is, to decide what functions should be automated and to what extent before a specific RAS is established. The information analysed for this case study is mainly derived from the author's robotic simulation analysis and experimental results. Information on wheel lathes has been gathered mainly through visits to depots, observations and conversations with engineers/operators. The purpose of the wheel lathe case study is to verify whether the framework can help to re-evaluate an already implemented system and thus propose guidance on whether the current allocation can be optimised.

Table 6-16 and Table 6-17 present the preliminary and final allocation decisions for the two case studies. The preliminary allocation is based on the updated Fitts list; it can be seen that after application of the railway maintenance function allocation framework, the final allocation decisions are not necessarily the same as those suggested by the updated Fitts list.

In the robotic inspection case study, the updated Fitts list states that machines are better at detection and perception, which implies allocating both visual search and NDI to automation. As can be seen from the review in Section 2.3, some detection and perception activities have been automated in the railway industry [69][70]. In this case study, the results for automated visual inspection do not provide sufficient accuracy to automate NDI; the framework gives the recommendation not to automate NDI from a system-wide perspective. The reason for the different allocation results is that the Fitts list is considered at the level of a single function, while railway maintenance systems are complex, composed of many sub-systems that interact with each other, so certain functions may be considered as not appropriate for automation.

In the second case study, however, the final decision result is essentially the same as the preliminary one. In this case, due to the lack of physical capability of humans (e.g., comparatively weak power output), positioning and machining are considered only able to be done by wheel lathe. For the 'measurement' and 'calculation' functions, the updated Fitts list suggests that automation can be invoked, and through the analysis of the framework, it is also considered that automation is indeed better.

Comparing the two case studies, the author believes that the updated Fitts list can be a good starting point but should not be directly used as a guideline to aid decision-making. As technology advances, there may be newer versions of the Fitts list. In this framework, it can also be updated accordingly.

As can be seen from the review in Section 2.6.3, most existing theories of functional allocation focus on only one aspect such as human behaviour[78] or system performance[80]; the robotic inspection case study also verifies that these single-aspect considerations are not applicable to complex railway systems. Even the visual search function is proved to be feasible and has the potential to improve system performance; the framework, however, considers the entire complex railway maintenance system and even takes into account different stakeholders, for example by calculating costs. The final decision is not to use visual robotic inspection.

Table 6-16 Robotic inspection cell allocation comparison

Function	Related human/machine capabilities listed in Fitts list	Preliminary allocation	Final allocation decision
Visual search	Ability to detect a small amount of visual or acoustic energy **(Machine)** Ability to perform repetitive routine tasks **(Machine)** Ability to reason inductively **(Human)**	Both machine and human involved	Human
NDI search	Ability to detect a small amount of visual or acoustic energy **(Machine)** Ability to perform repetitive routine tasks **(Machine)**	Both machine and human involved	Human

	Ability to reason inductively **(Human)**		
Decision	Ability to reason inductively **(Human)** Ability to exercise judgement **(Human)** Ability to reason deductively, including computational ability **(Machine)**	Both machine and human involved	Human

Table 6-17 Wheel lathe allocation comparison

Function	**Related human/machine capabilities listed in Fitts**	**Preliminary allocation**	**Final allocation decision**
Positioning	Ability to perform repetitive routine tasks **(Machine)** Apply great force smoothly and precisely **(Machine)**	Machine	Machine
Pre-measurement	Ability to perform repetitive routine tasks **(Machine)**	Machine	Machine
Calculation	Ability to reason inductively **(Human)** Ability to reason deductively, including computational ability **(Machine)**	Both human and machine involved	Machine

Machining	Ability to perform repetitive routine tasks **(Machine)**	Machine	Machine
Re-measurement	Ability to perform repetitive routine tasks **(Machine)**	Machine	Machine
Decision	Ability to reason inductively **(Human)** Ability to exercise judgement **(Human)**	Human	Human

These two case studies demonstrate that the framework can derive allocation advice for different types of scenarios, systems and functions in rollingstock maintenance. The framework does not show a subjective preference for whether to allocate a task to humans or to automate it. Rather, it is further optimised through iterative analysis, resulting in an allocation that is relatively optimised and suitable for the railway maintenance environment.

The analysis of this entire chapter concludes that the framework has the following merits.

1. Previous function allocation theories consider allocation from only one aspect. This comprehensive framework considers allocation decisions in three aspects (feasibility, system performance and cost) in order to make more prudent and comprehensive decisions.
2. RAS and humans have their own strengths; an updated Fitts list is introduced to compare the performance of RAS and humans, respectively, during the preliminary system design stage.
3. Automation is always associated with human factors. Especially for a safety-critical industry, human trust in automation is the major issue affecting usage [21]. Information on human trust in machines can be obtained through conversations/questionnaires with operators working in

the depot. In the wheel lathe case study, human trust is taken into consideration in terms of allocation of the ‘calculation’ function.

CHAPTER 7 CONCLUSIONS AND FUTURE PERSPECTIVES

7.1 General summary and present contributions

Maintenance is a major and integrated part of the railway operation. In spite of numerous advancements in delivering more intelligent and reliable maintenance systems, the industry continuously faces major challenges including labour intensity, hazardous working conditions and low efficiency. Regardless of restrictions such as system complexity and costs, RAS is a potentially attractive tool to improve railway maintenance performance. The hypothesis of this research is that with appropriate function allocation decisions, the application of RAS could help the railway industry to improve rolling stock maintenance practice. To test this hypothesis, the author has considered the following content.

- The background knowledge has been presented, and the theoretical foundation laid to support this study.

Chapter 1 introduced the importance of railway maintenance, current maintenance situations of UK railways, and the challenges of railway maintenance automation. It considered the cruciality of maintenance in ensuring safe, efficient and reliable operations and how maintenance further enhances the availability of the UK railways. At the system design stage, exploring 'what functions to automate?' is generally more significant than 'how to achieve automation?' The decision of human–machine function allocation has direct effects on how maintainers perform a task. Therefore, it is necessary to reach a decision on what and to what extent tasks should be automated in railway maintenance systems. Chapter 2 introduced railway maintenance theories and reviewed RAS applications applied both inside and outside the rail industry as well as the existing function allocation methods. This chapter demonstrated that successfully implementing an RAS requires feasible and appropriate function allocation in the human–machine system design. Still, there is a research gap in applying function allocation in the railway environment. Current existing function allocation models are generally inexhaustive. Furthermore, they are all designed for specific systems such as aerospace human–computer control interfaces which might result in limited applicability in railway maintenance.

- To address the research gap, the author has designed, applied and validated a novel railway maintenance function allocation framework.

Due to the complexity of railway systems, Chapter 3 proved the suitability of multi-criteria decision-making in adapting to the function allocation framework by meeting various requirements such as improving maintenance efficiency to further improve railway capacity, reduce cost and human errors. This chapter started with an introduction to the decision-making methods used in systems engineering. Then, the MCDM process was further discussed and illustrated with a practical railway industry example.

Chapter 4 highlighted the characteristics of railway maintenance, which are complex systems with various uncertainties. Accordingly, evaluation criteria were derived, to be used in the framework evaluation phase. The chapter first discussed different environment types and ultimately defined railway maintenance as a semi-structured environment which implies a technical challenge. Consequently, feasibility was chosen as the primary evaluation criterion to help with the preliminary maintenance system design. RAMS and costs were also discussed and ultimately identified as critical measures for maintenance system evaluation.

Based on the function allocation theories, MCDM process and criteria, the final novel railway function allocation framework design was presented in Chapter 5 which forms the core of this work.

The proposed framework includes comprehensive considerations from various aspects to provide systematic guidance for function allocation in the preliminary stages of designing an automatic maintenance system. It proposes a novel task analysis method which incorporates ergonomics into the maintenance task analysis phase to provide the preliminary allocation. Afterwards, the framework utilises a multi-stage evaluation approach to assess the criteria selected in Chapter 4, which are the technical feasibility, overall system performance and cost impact. It is worth noting that MCDM is adopted into system performance analysis phases to trade off the overall system performance among four criteria (Reliability, Availability, Maintainability, Safety). Function allocation is accomplished in an iterative way to ensure that all sub-tasks are taken into account. The structure of the framework is supported by rigorous derivations and verified by practical examples.

To demonstrate and verify the framework, wheelset maintenance was selected as a typical railway maintenance example. The first case study focused on the automation of wheelset inspection. The updated Fitts list states that machines are better at detection and perception, which implies allocating both visual search and NDI to automation. Since robotic inspection is not yet used in industrial maintenance depots, a real KUKA robotic inspection system has been built in the lab. Inspection tasks were analysed, followed by a feasibility study, system performance evaluation and cost analysis. This case study also integrated analysis elements such as FTA and cost analysis. The end of the iterative process is to derive the final system design suggestion which is not to automate wheelset inspection from a system-wide perspective. The second case study presented a wheel lathe system for wheel profiling. The purpose of this case study is to verify whether the framework can help to re-evaluate an already implemented system and thus propose guidance on whether the current allocation can be optimised. Again, followed by task analysis, preliminary allocation, evaluation processes (feasibility, system performance and cost), the framework considered that automated wheel lathe system is indeed better.

The two case studies demonstrated the process of how the function allocation framework is applied and verified the framework helps decision-making in function allocation for wheelset maintenance.

Review and summarise the objectives listed in Chapter 1.3.

a) To identify the current railway maintenance environment, maintenance processes, maintenance challenges and how RAS can assist.

Section 1.1 and 1.2 outlined the current maintenance challenges and listed the advantages of introducing RAS into railway maintenance. Section 2.2 and 5.2 both gave examples of maintenance processes. Section 4.1 presented the author's analysis and definition of railway environment.

b) To identify the evaluation criteria for rolling stock maintenance systems.

Based on the railway environment features, the selection of evaluation criteria was elaborated from the perspective of definitions, analysis tools and railway application practices which is presented in section 4.2, section 4.3 and section 4.4. Finally, three evaluation criteria were identified: feasibility, system performance and cost.

c) To study how practical it is for RAS to be implemented in a rolling stock depot, it is important to review existing railway RAS applications as well as existing automated manipulation systems.

Section 2.5 reviewed the RAS applications in railway systems and an example of developed robotic cell that demonstrated the technical feasible of RAS in railway and inspection systems.

d) To identify existing function allocation theories in other industries and how these could be transferred to railway practices.

Section 2.6 provided a review, analysis and discussion of function allocation theories. Based on the review, it can be concluded that there is a lack of research in function allocation methods that can be applied in railway maintenance systems. However, the updated Fitts list is suitable for the preliminary stage of railway maintenance allocation, as discussed in section 2.6.1 and 5.1.1.

e) To develop and demonstrate a novel framework to support decision-making in railway maintenance function allocation.

The final design of the novel railway function allocation framework was presented in Chapter 5. In order to demonstrate and evaluate the framework, two case studies were presented in Chapter 6. A critical review of the framework was presented in section 6.3.

In summary, the objectives listed have proved to be achieved.

7.2 Future work and recommendations

Future work based on the present study can be continued in the following paths.

Further function allocation research beyond maintenance and framework enhancement

Automation applications in railway are not limited to maintenance. For example, automatic train operation (ATO) [200] and automatic train control systems [201] could also be considered. To achieve optimum system performance, function allocation needs to be considered. One further suggestion is that other railway systems can be investigated. As railway applications have various features, the selection criteria and the level of importance may vary from case to case. It is thus beneficial to validate these other key performance indicators, e.g. capability, carbon, customer satisfaction and cost (4Cs).

The purpose of this research was to investigate rolling stock maintenance. Therefore, the function allocation framework only applies in rolling stock scenarios; infrastructure maintenance is not considered but could be further integrated into the framework. When considering infrastructure maintenance function allocation, the maintenance demands need to be reidentified and criteria evaluation phases need to be redesigned accordingly.

Further development of the robotics system

As mentioned in Chapter 6, a robotic inspection cell has been developed for the autonomous inspection of railway wheelsets. However, as the environment navigation techniques can adapt to semi-structured environments, the cell may also be applied to inspect other objects such as bearings and gear boxes.

APPENDIX[191]

Error producing conditions

Area	Ref	Error producing condition	Max. affect
Task design	T1	Unfamiliarity with a situation which is potentially important, but which only occurs infrequently, or which is novel.	17
	T2	A shortage of time available for error detection and correction	
	T3	A need to unlearn a technique and apply one which requires the application of an opposing philosophy.	8
	T4	The need to transfer specific knowledge from task to task without loss.	5.5
	T5	An impoverished quality of information conveyed by person/person interaction.	3
	T6	Little or no independent checking or testing of output.	3

	T7	A conflict between immediate and long-term objectives.	2.5
	T8	Unclear allocation of function and responsibility.	1.6
	T9	A danger that finite physical capabilities will be exceeded.	1.4
	T10	Prolonged inactivity or highly repetitious cycling of half hour low mental workload tasks.	1.1
Interface	In1	A low signal-noise ratio.	10
	In2	A means of suppressing or over-riding information of features which is too easily accessible.	9
	In3	No means of conveying spatial and functional information to operators in a form which they can readily assimilate.	8
	In4	A mismatch between an operator's model of the world and that imagined by a designer.	8

	In5	No obvious means of reversing an unintended action.	8
	In6	A channel capacity overload, particularly one caused by simultaneous presentation of non-redundant information.	6
	In7	Poor, ambiguous or ill-matched system feedback.	4
Competence management	C	Operator inexperience.	3
Procedures	PR1	Ambiguity in the required performance standard.	5
	PR2	An impoverished quality of information conveyed by procedures.	3
Person	P1	A mismatch between perceived and real risk.	4
	P2	Fatigue from shift and work patterns.	2.6
	P3	High level emotional stress.	2
	P4	Little opportunity to exercise mind and body outside the immediate confines of a job.	1.8

	P5	Little or no intrinsic meaning in a task.	1.4
	P6	Low workforce morale.	1.2
Environment	E	A poor or hostile environment.	8

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