LET'S AUGMENT THE FUTURE TOGETHER!

AUGMENTED REALITY TROUBLESHOOTING SUPPORT FOR IT/OT ROLLING STOCK FAILURES

Sara Scheffer

Let’s augment the future together!

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Summary

The railway industry is moving to a socio-technological system that relies on computer-controlled and human-machine interfaces. Opportunities arise for creating new services and commercial business cases by using technological innovations and traffic management systems. The convergence of Information Technology (IT) with Operational Technology (OT) is critical for cost-effective and reliable railway operations. However, this convergence introduces complexities, leading to more intricate rolling stock system failures. Hence, operators necessitate assistance in their troubleshooting and maintenance strategy to simplify the decision-making and action-taking processes. Augmented Reality (AR) emerges as a pivotal tool for troubleshooting within this context. AR enhances the operator's ability to visualize, contextualize, and understand complex data by overlaying real-time and virtual information onto physical objects. AR supports the identification of IT/OT rolling stock system failures, offers troubleshooting directions, and streamlines maintenance procedures, ultimately enhancing decision-making and action-taking processes.

This research investigates how AR can support operators in navigating troubleshooting and maintenance challenges posed by IT/OT rolling stock system failures in the railway industry. A comprehensive investigation within the Dutch railway sector over four years led to the development and validation of various conceptual and technological solutions.

The scientific cases and industrial context presented led to the main research question addressed in this thesis: *"How to use AR to support operators in troubleshooting and maintaining IT/OT converged rolling stock systems faced by the railway industry?"* To examine this research question, the thesis focuses on the following five themes that were based on a mixed-method pragmatic approach aimed at clarifying, describing, and prescribing the research:

- Theme I: Foundation of AR in maintenance
- Theme II: Operator 4.0: Perspective and decision-making
- Theme III: Backbone for AR troubleshooting: Front-end and back-end
- Theme IV: Functionality of AR troubleshooting
- Theme V: Organizational impact

Within each theme, various research topics are explored using a well-balanced combination of qualitative and experimental research methodologies. The findings and insights gained from these research topics contributed to a comprehensive understanding of the tools and methods crucial for facilitating AR troubleshooting support, thereby addressing the main research question.

The first theme explores research challenges and future directions for the application of AR in complex environments. It highlights the versatility of AR, showcasing its potential utilization across various rolling stock maintenance operations.

The second theme centres on the operator's perspective and the associated decision-making process. This theme introduces an adaptive architectural framework designed to capture operator knowledge, support maintenance tasks, conduct comprehensive failure analysis, offer problem-solving strategies, and enhance learning capabilities by documenting procedural tasks. Furthermore, the framework is suitable for preliminary training on new or intricate maintenance procedures. Operators are provided decision-making support through a comprehensive approach, involving the extracting, filtering, structuring, and translating of data and pertinent information from a developed centralized data platform. This support extends to capturing real-life system information using object recognition, presenting troubleshooting directions through what-if analysis, and tracking operator activities to develop future maintenance operations.

Differing from the initial two themes, the third theme takes a more fundamental approach centred on Artificial Intelligence (AI), specifically emphasizing the integration of AR and AI. It introduces a dynamic reference map encompassing Knowledge-Based Systems (KBS), AI, and AR, offering a hybrid solution that connects Machine Learning (ML) with AR for adaptive fault detection. Additionally, this theme proposes a robust database architecture serving as the backbone for discovering maintenance patterns and providing troubleshooting directions through pre-processing maintenance data utilizing ML data mining tools. The AR troubleshooting system delivers structured information extracted from instances of rolling stock system failure.

The fourth theme integrates both functionality and User Interface (UI) requirements to collectively enhance AR troubleshooting. Beyond the research's emphasis on the functionality of AR troubleshooting, design guidelines play a crucial role, dictating how troubleshooting tools should be developed by integrating valuable input from operators. A crucial aspect involves integrating real-time maintenance information with existing fault-diagnosing strategies while ensuring that the UI is tailored to provide effective human-AR collaboration.

Ultimately, the concluding theme of this research focuses on the practical application of an AR troubleshooting tool within railway organizations. A presented organizational AR roadmap offers insight, enabling a railway organization to gain a deeper understanding of the essential technical and organizational elements crucial for successful AR integration.

To conclude, this research addresses a gap in the existing literature by exploring the use of AR for troubleshooting IT/OT rolling stock failures. The study introduces an innovative approach integrating AR, information systems, and maintenance principles to support troubleshooting IT/OT system failures. Through AR troubleshooting, utilizing an adaptive architectural framework, ML, and a centralized data platform, the research contributes to fault diagnosing and decision-making procedures in rolling stock maintenance. Simultaneously, it elevates the level of collaboration between operators and AR. Conducted in collaboration with the Dutch railway sector, the study's insights and results are generalizable to other domains dealing with IT/OT convergence, providing a roadmap for organizations to implement AR in maintenance procedures.

Samenvatting

De spoorwegindustrie evolueert naar een socio-technologisch systeem dat steunt op computergestuurde en mens-machine interfaces. Er ontstaan kansen voor het creëren van nieuwe diensten en commerciële business cases door gebruik te maken van technologische innovaties en verkeersmanagementsystemen. De convergentie van informatietechnologie (IT) met operationele technologie (OT) is cruciaal voor kosteneffectieve en betrouwbare spoorwegactiviteiten. Deze convergentie introduceert echter complexiteit, wat leidt tot meer ingewikkelde storingen aan rollend materieel. Daarom hebben machinisten hulp nodig bij het oplossen van problemen en bij hun onderhoudsstrategie om de besluitvorming en het nemen van maatregelen te vereenvoudigen. Augmented Reality (AR) komt in deze context naar voren als een cruciaal hulpmiddel voor probleemoplossing. AR verbetert het vermogen van de monteur om complexe gegevens te visualiseren, in context te plaatsen en te begrijpen door real-time en virtuele informatie over fysieke objecten te leggen. AR ondersteunt de identificatie van storingen in IT/OT-systemen voor rollend materieel, biedt aanwijzingen voor het oplossen van problemen en stroomlijnt onderhoudsprocedures, wat uiteindelijk de besluitvorming en het nemen van actie verbetert.

In dit onderzoek wordt onderzocht hoe AR monteurs kan ondersteunen bij het oplossen van problemen en het oplossen van onderhoudsproblemen als gevolg van storingen aan IT/OT-systemen in de spoorwegsector. Een uitgebreid onderzoek binnen de Nederlandse spoorwegsector gedurende vier jaar leidde tot de ontwikkeling en validatie van verschillende conceptuele en technologische oplossingen.

De gepresenteerde wetenschappelijke cases en industriële context leidden tot de belangrijkste onderzoeksvraag in dit proefschrift: *"Hoe kan AR worden gebruikt om monteurs te ondersteunen bij het oplossen en onderhouden van IT/OT geconvergeerde rollend materieelsystemen waarmee de spoorwegindustrie wordt geconfronteerd?"*. Om deze onderzoeksvraag te onderzoeken, richt het proefschrift zich op de volgende vijf thema's die gebaseerd zijn op een gemengde methodologische aanpak gericht op het verduidelijken, beschrijven en voorschrijven van het onderzoek:

- Thema I: Fundament van AR in onderhoud
- Thema II: Operator 4.0: Perspectief en besluitvorming
- Thema III: Ruggengraat voor AR troubleshooting: Front-end en back-end
- Thema IV: Functionaliteit van AR troubleshooting
- Thema V: Organisatorische impact

Binnen elk thema zijn verschillende onderzoeksonderwerpen onderzocht met behulp van een uitgebalanceerde combinatie van kwalitatieve en experimentele onderzoeksmethoden. De bevindingen en inzichten die zijn verkregen uit deze onderzoeksonderwerpen hebben bijgedragen aan een beter begrip van de tools en methoden die cruciaal zijn voor het faciliteren van ondersteuning bij AR troubleshooting, waarmee de belangrijkste onderzoeksvraag is beantwoord.

Het eerste thema verkent onderzoek uitdagingen en toekomstige richtingen voor de toepassing van AR in complexe omgevingen. Het belicht de veelzijdigheid van AR en laat zien hoe het kan worden ingezet bij verschillende onderhoudswerkzaamheden aan rollend materieel.

Het tweede thema richt zich op het perspectief van de monteur en het bijbehorende besluitvormingsproces. Dit thema introduceert een adaptief architectonisch raamwerk dat is ontworpen om kennis van de monteur vast te leggen, onderhoudstaken te ondersteunen, uitgebreide storingsanalyses uit te voeren, strategieën voor probleemoplossing te bieden en het leervermogen te vergroten door procedurele taken te documenteren. Bovendien is het raamwerk geschikt voor voorbereidende training op nieuwe of ingewikkelde onderhoudsprocedures. Monteurs krijgen ondersteuning bij het nemen van beslissingen via een uitgebreide aanpak, waarbij gegevens en relevante informatie uit een ontwikkeld gecentraliseerd gegevensplatform worden gehaald, gefilterd, gestructureerd en vertaald. Deze ondersteuning strekt zich uit tot het vastleggen van echte systeeminformatie met behulp van objectherkenning, het presenteren van aanwijzingen voor probleemoplossing door middel van wat-als-analyse en het volgen van activiteiten om toekomstige onderhoudswerkzaamheden te ontwikkelen.

In tegenstelling tot de eerste twee thema's, volgt het derde thema een meer fundamentele benadering gericht op kunstmatige intelligentie (AI), waarbij de nadruk ligt op de integratie van AR en AI. Het introduceert een dynamische referentiekaart die kennis gebaseerde systemen (KBS), AI en AR omvat en een hybride oplossing biedt die Machine Learning (ML) verbindt met AR voor adaptieve foutdetectie. Daarnaast wordt in dit thema een robuuste databasearchitectuur voorgesteld die als ruggengraat dient voor het ontdekken van onderhoudspatronen en het geven van aanwijzingen voor probleemoplossing door het vooraf verwerken van onderhoudsgegevens met behulp van ML-dataminingtools. Het AR-systeem voor probleemoplossing levert gestructureerde informatie afkomstig van storingen in het rollend materieel.

Het vierde thema integreert zowel functionaliteit als gebruikersinterface (UI) vereisten om samen AR troubleshooting te verbeteren. Naast de nadruk die het onderzoek legt op de functionaliteit van AR troubleshooting, spelen ontwerprichtlijnen een cruciale rol, die dicteren hoe tools voor troubleshooting moeten worden ontwikkeld door waardevolle input van monteurs te integreren. Een cruciaal aspect is de integratie van real-time onderhoudsinformatie met bestaande strategieën voor foutdiagnose, waarbij ervoor wordt gezorgd dat de gebruikersinterface is afgestemd op een effectieve samenwerking tussen mens en AR.

Uiteindelijk richt het slotthema van dit onderzoek zich op de praktische toepassing van een AR-tool voor probleemoplossing binnen spoorwegorganisaties. Een gepresenteerde organisatorische AR-roadmap biedt inzicht, waardoor een spoorwegorganisatie een beter begrip krijgt van de essentiële technische en organisatorische elementen die cruciaal zijn voor een succesvolle AR-integratie.

Concluderend, dit onderzoek voorziet in een leemte in de bestaande literatuur door het gebruik van AR te onderzoeken voor het oplossen van IT/OT storingen aan rollend materieel. Het onderzoek introduceert een innovatieve aanpak die AR, informatiesystemen en onderhoudsprincipes integreert ter ondersteuning van het oplossen van storingen aan IT/OT-systemen. Door middel van AR probleemoplossing, gebruikmakend van een adaptief architectonisch kader, ML en een gecentraliseerd dataplatform, draagt het onderzoek bij aan foutdiagnose en besluitvormingsprocedures bij het onderhoud van rollend materieel. Tegelijkertijd wordt het niveau van samenwerking tussen monteurs en AR verhoogd. De inzichten en resultaten van het onderzoek, dat is uitgevoerd in samenwerking met de Nederlandse spoorwegsector, zijn te verschalen naar andere domeinen die te maken hebben met IT/OT-convergentie en bieden een routekaart voor organisaties om AR te implementeren in onderhoudsprocedures.

Glossary

Notion	Description
Adaptive Architectural Framework	A flexible and dynamic structure that can evolve or adapt to changing requirements and conditions.
AR Database Architecture	A structure and organization of databases specifically designed to support AR troubleshooting procedures.
AR Gateway	A component that facilitates communication and data exchange between AR systems and other devices or databases.
AR Roadmap	An outline of a strategic plan or timeline for the implementation of AR technologies within an organization or industry.
Artificial Intelligence (AI)	The development of computer systems that can perform tasks that typically require human intelligence. In troubleshooting system failures, AI is applied to design algorithms that analyse complex data, identify patterns, and make decisions to diagnose and address issues.
Augmented Reality (AR)	A technology that overlays computer-generated information, such as images, sound, or (3D) data, onto the real-world environment, enhancing the user's perception and interaction with the surroundings.
Case-Based Reasoning (CBR)	A problem-solving approach that involves solving new problems based on solutions to similar problems stored as bases in a knowledge base.
Centralized Data Platform	A unified system that collects, processes, and manages data from various sources in a centralized location, providing a comprehensive view and facilitating analysis.
Cloud-Based Computing	The delivery of computing services, such as storage, processing, and software, over the internet, offering flexibility, scalability, and adaptability.
Computer-Aided Design (CAD)	The use of computer technology to assist in the creation, modification, analysis, or optimization of a design.
Configuration Backbone	A central structure or system that manages and organizes the configuration of components within a larger system.
Controller Area Network (CAN)	A communication standard used in rolling stock and industrial applications for real-time data exchange between electronic control units.
Convolutional Neural Networks (CNN)	Type of deep neural network specifically designed for image recognition and processing, using convolutional layers to capture hierarchical patterns.
Cyber-Physical Systems (CPS)	Integrated systems that bridge the physical and computational worlds, combining hardware and software to monitor, control, and respond to the physical environment.
Decision-Making	The process of selecting a course of action from available alternatives based on analysis, evaluation, and consideration of relevant information and factors.
Deep Learning (DL)	A subfield of ML that involves neural networks with multiple layers. It is particularly effective in handling complex data representations.

Notion	Description
Digital Twin (DT)	A virtual representation of a physical object, system, or process. It mirrors the real-world entity in digital form, providing a means to monitor, analyse, and simulate its behaviour.
Dynamic Reference Map	A continuously updated map that provides real-time information.
Failure Mode Effect Analysis (FMEA)	A systematic approach to identify and assess potential failure modes in a system, prioritizing them based on their impact and likelihood.
Fault Tree Analysis (FTA)	A method used to analyse and visualize the potential causes of a system failure by constructing a logical diagram of events and their relationships.
Functional Blocks	Modular components that perform specific functions within a system or process.
Hand-Held Device (HHD)	A portable electronic device that can be held in the hand and operated for various purposes, such as communication, data input, or information retrieval.
Head-Mounted Display (HMD)	A wearable technology that is worn on the head to provide an immersive audio-visual experience.
Industry 4.0	Represents the integration of advanced technologies, such as IoT, AI, AR, and automation into manufacturing processes to create “smart factories” with improved efficiency and flexibility.
Information Control Engine	Responsible for reasoning and drawing conclusions based on the information stored in the knowledge base. It interprets the knowledge, applies logical rules, and derives new insights or solutions to problems.
Information Inference	Responsible for managing and regulating the flow and accessibility of information within a system.
Information Technology (IT)	The use, development, and management of computer systems, software, and networks to store, process, transmit, and retrieve information.
Internet of Things (IoT)	The network of interconnected physical devices, vehicles, appliances, and other objects embedded with sensors, software, and connectivity to exchange data.
Interpretive Structural Modelling (ISM)	A method used to analyse and represent the relationships among various elements in a system, helping to identify hierarchical structures.
Knowledge-Based Systems (KBS)	A type of AI system that utilizes explicit knowledge and reasoning mechanisms to solve problems and make decisions.
Logistic Regression (LR)	A statistical method used for binary classification. It is employed in classification tasks and assumes independence among features.
Machine Learning (ML)	A subset of AI that involves the development of algorithms and models that enable computers to learn from data and improve their performance on a specific task over time. In troubleshooting, ML algorithms can be trained on historical data to recognize patterns and trends, aiding in the prediction of system failures and facilitating data-driven decision-making.

Notion	Description
Maintenance, Repair, and Overhaul (MRO)	Activities performed to maintain, repair, or overhaul equipment or systems to ensure their proper functioning.
Manual pre-processing data (MPD)	The manual preparation and cleaning of data before analysis, including tasks such as data cleaning, transformation, and feature engineering.
Maturity Model and Readiness Assessment	A method for evaluating an organization's readiness and maturity in adopting specific practices or technologies.
Naïve Bayes (NB)	A probabilistic ML algorithm based on Bayes' theorem. Commonly used for classification tasks and assumes independence among features.
Natural Language Processing (NLP)	A field of AI focused on enabling computers to understand, interpret, and generate human language.
Operational Technology (OT)	The use of technology in industrial operations and control systems focuses on the monitoring and control of physical devices and processes.
Operator 4.0	The modernized and digitized version of an operator in the Industry 4.0 context. It involves the integration of advanced technologies, data analytics, and connectivity to enhance the capabilities of operators in industrial settings.
PrefixSpan	Sequential pattern mining algorithm used to discover frequent patterns or sequences in sequential data.
Reliability Centred Maintenance (RCM)	Maintenance strategy focused on optimizing maintenance efforts by prioritizing tasks based on the criticality and reliability of equipment.
Root Cause Analysis (RCA)	A systematic process of identifying and addressing the underlying causes or problems or incidents, aiming to prevent their recurrence.
Sequential Augmented Reality Assist (SARA)	A specific application or system that provides step-by-step AR guidance or assistance to users, typically in tasks or processes.
Support Vector Machine (SVM)	An ML algorithm is used for classification and regression tasks. It works by finding the hyperplane that best separates data points into different classes.
Term Frequency-Inverse Document Frequency (TF-IDF)	A numerical statistic is used in NLP and information retrieval to evaluate the importance of a word within a document relative to a collection of documents.
Troubleshooting	The process of identifying, diagnosing, and resolving problems or issues within a system, device, or process. It involves systematically analysing symptoms, identifying potential causes of the problem, and implementing solutions to restore the system to normal operation.
User Interface (UI)	The point of interaction between a user and a computer system, including elements such as screens, pages, and graphical controls.

List of publications

This thesis is composed of the following publications.

No.	Title	Status	Contribution to
1.	Augmented reality for IT/OT failures in maintenance operations of digitized trains: current status, research challenges and future directions	Published	Procedia CIRP of the 31^{st} CIRP Design Conference 2021
2.	How to make augmented reality a tool for railway maintenance operations: Operator 4.0 perspective	Published	MDPI Applied Sciences
3.	Supporting maintenance operators using augmented reality decision-making: visualize, guide, decide & track	Published	Procedia CIRP of the 33^{rd} CIRP Design Conference 2023
4.	Troubleshooting: a dynamic solution for achieving reliable fault detection by combining augmented reality and machine learning	Published	Proceedings of The 10^{th} International Conference on Through-Life Engineering Services
5.	Augmented reality database architecture: the backbone for IT/OT rolling stock maintenance	Under review	Advanced Engineering Informatics
6.	Using functional blocks for rolling stock troubleshooting: sequential augmented reality assistant (SARA)	Under review	IEEE Access
7.	Developing AR design guidelines for troubleshooting rolling stock system failures: Industrial prototyping and human factors	Under review	Journal of Quality in Maintenance Engineering
8.	An augmented reality roadmap for rolling stock organizations	Finalized	Thesis chapter

Chapter 1 – General introduction

1.1 Introduction

The railway industry is moving towards a complex socio-technological system that relies on computer-controlled and human-machine interfaces. Modern rolling stock is equipped with digital technologies, sensors, and high-tech communication systems [1]. This digitization enables the collection of vast amounts of data related to the performance, health, and condition of rolling stock components in real time. Rolling stock digitization leads to an increase in data complexity, requiring advanced maintenance and troubleshooting approaches. Traditional maintenance and troubleshooting methods become insufficient due to the volume and complexity of data generated, making it challenging for maintenance operators to diagnose and address system failures efficiently [2]. The operators at the troubleshooting, repair, and maintenance stages face difficulties in understanding the failure of the rolling stock system due to its variance. The rapid advancements in technologies and the complexity of maintenance and troubleshooting procedures demand flexible guidance to operators in industrial environments [3]. The challenges posed by increased digitization drive the utilization of new technologies, including Internet of Things (IoT), Artificial Intelligence (AI), cloud-based computing, and Augmented Reality (AR) [1]. New technologies are designed to handle large datasets, automate decision-making processes, and enhance the overall efficiency of maintenance operations. AR is a technology that provides a visual and interactive overlay of digital information onto the real-world environment, offering operators real-time guidance and enhanced decision support during troubleshooting. AR is identified as a technology that can complement digitization and other advancements for troubleshooting in industrial settings, including rolling stock maintenance [4]. AR can guide the operators towards understanding the identified problem and improve product life, supporting technology transfer at various stages in the rolling stock life [3].

AR is a versatile technology that provides a significant level of flexibility, facilitating the transfer of rolling stock system information and guiding operators during maintenance, troubleshooting, and repair. The railway sector foresees that utilizing AR solves rolling stock failures faster, increasing rolling stock availability and usability [5]. Recognizing the impact AR has on maintenance procedures, this thesis examines the use of AR for troubleshooting rolling stock failures, particularly troubleshooting and maintaining digitized system failures. More specifically, it examines the usage of AR for converged Information Technology (IT) and Operational Technology (OT) systems by troubleshooting rolling stock failures in the railway sector. The research is conducted in the Dutch railway sector for approximately four years, where the researcher collaborates with the Netherlands Railways (NS) which is the largest provider of passenger services in the Netherlands.

The rest of this chapter provides an introductory overview of this thesis's research, the various themes covered, and the research approach. The introduction is divided into seven sections. First, in section 1.2, the theoretical background highlights the rolling stock maintenance complexity and the foundations for using AR for maintenance operations. In section 1.3, the industrial context covering the technological developments in the Dutch railway sector is introduced. Subsequently, in section 1.4, the motivation for this research is discussed. Section 1.5 presents the research goal and the research questions (RQ) addressed in this thesis. Section 1.6 provides an overview of the research methods and methodologies used. Finally, the reading guide of the thesis is provided in section 1.7.

1.2 Theoretical background

1.2.1. Rolling stock maintenance complexity

Railway systems are facing a wide range of transformations that bring a new competitiveness to the sector and efficient maintenance of railway operations must play an important role in such transformation. Rolling stock maintenance plays a pivotal role in ensuring operational availability throughout the rolling stock lifecycle. However, this process comes with substantial costs, exposes operators to challenging conditions, and is susceptible to inconsistencies and inaccuracies [6]. The expenses associated with maintenance constitute a substantial portion of the overall lifecycle costs of rolling stock, frequently surpassing the initial investment costs [7]. Furthermore, the maintenance procedure is often characterized by non-uniformity, lack of determinism, and a lack of standardization [8]. AR can address this by offering a more streamlined and standardized approach by providing real-time guidance, information overlays, and interactive support.

The imperative for IT/OT convergence in the railway industry stems from the urgent need to modernize and optimize operations in response to the growing demands for performance and service. The growing European railways, driven by the performance and service needs to shift more passengers and cargo from roads to the railways for emission reduction targets, have focused on digitizing rail operations [9]. The digital transformation involves creating a fully connected technology stack that allows for complete control of rail operations, including the digitization of rolling stock [9]. As a consequence of digitizing rolling stock, there is an increase in the implementation of both IT and OT systems, converging into the rolling stock itself. The integration of IT/OT systems represents a significant leap forward in railway operations, promising improved reliability, efficiency, and safety, thereby making a substantial contribution to the overall advancement of the railway industry. Yet, numerous challenges hinder the broad adoption of IT/OT convergence, including the integration of disparate communication protocols and data formats, the need to retrofit existing systems, and the integration within organizational structures. The transformation necessitates the adoption of modern technologies, such as AI, AR, IoT, and cloud-based computing, for (remote) inspections and utilizing data to enhance efficiency.

The resilience of a railway system is measured by its ability to withstand and adapt to various changes, disruptions, or perturbations such as the increase in passenger demand, unexpected technical issues, or disruptions in the overall transport network. Complexity science, an interdisciplinary field that studies complex and dynamic systems, is often invoked in understanding systems that are intricate and

interconnected, such as railway networks, where the behaviour of the system is influenced by multiple factors. Research on the convergence of IT with OT systems in rolling stock and utilizing AR for maintenance and troubleshooting procedures contribute to research themes of “Engineering for a resilient world” and “Engineering our digital society” [10]. IT/OT convergence is highly complex and caused by largely intangible data flows, misalignment with the physical asset, and lack of knowledge management, and organizational coherence. Unfortunately, there is no simple way to overcome the technical and organizational challenges of IT/OT convergence. Harmonization or alignment of maintenance integration, processes and organization of IT and OT and support systems are required strategic research directions [7][11]. Early awareness of convergence dictates the correct maintenance approach, should be a multi-disciplinary practice involving expertise from various fields, and should take the life cycle of the rolling stock into account.
This holistic approach ensures that maintenance and troubleshooting decisions are not only reactive but also proactive, taking into account the evolving nature of the technology and systems within the rolling stock throughout its entire lifespan.

1.2.2. New digitization approach for rolling stock maintenance

Industry 4.0 refers to the fourth industrial revolution and represents the integration of digital technologies, the IoT, data exchange, and automation into manufacturing processes [28]. The fundamental changes brought by Industry 4.0 technologies in maintenance, industries such as aerospace, defence, nuclear, wind turbine, and railways are focused on how to leverage these technologies. Industry 4.0 concepts in maintenance across these industries highlight the universal trends of leveraging data, automation, and connectivity to enhance operational efficiency [12]. The primary focus zeroes in on AR, with AI also falling within the scope of exploration. AI supports rolling stock maintenance by analysing real-time big data from sensors and other sources, detecting anomalies or deviations from normal behaviour, and performing Root Cause Analysis (RCA) to monitor, analyse, and predict the health state and the condition of rolling stock components [13]. Cyber-Physical Systems (CPS) integrate the digital and physical world, merge computer-based algorithms and networking capabilities with physical entities. This integration serves to optimize efficiency, automation, and decision-making within systems that involve both digital and physical components. The relevance of AR for maintenance in rolling stock becomes prominent in this research, by aligning the broader trend of exploiting data-based fault diagnosing and decision-making procedures. Integrating AI, CPS, and AR can support the automation of diagnosing, inspections, and failure predictions by providing maintenance operators with real-time AI-driven insights overlaid on physical components [14].

In several industries, such as the railway industry, there has been a recent shift to service-based models. In this approach, the rolling stock is leased to the end user, and a maintenance provider is contracted to ensure the availability and functioning of the rolling stock [11][15]. This shift to service-based models may lead to a situation where the owner of the rolling stock lacks the knowledge to address system errors independently. Many design strategies exist in trying to reduce through-life costs, such as striving for the integration of robustness and self-healing into machine designs [16]. The railway industry needs to improve maintenance practices on a broad level to keep high safety standards and achieve higher availability of rolling stock with less costs. Instead of depending solely on the maintenance provider's expertise in rolling stock maintenance and focusing on building robust systems and identifying failures, AR can play a role by providing a context for and visualizing failures.

In recent decades, there has been a growing utilization of AR in maintenance processes by offering operators assistance, simulation, and support to improve industrial processes even before integration into a maintenance environment [17][18]. AR-integrated toolsets support real-time monitoring and guided troubleshooting scenarios are presented in various streams of literature [7][19]. Continued research and development may focus on enhancing the capabilities of fault detection systems by incorporating Machine Learning (ML) algorithms. In addition, future work involves the integration of real-time data from automated fault detection systems into centralized data platforms and guiding the design of the AR User Interface (UI) experience. In traditional maintenance operations, operators manually note down information on rolling stock failures and perform activities in text instruction [20][21]. However, AR enables the operator to generate a digitized data report using the existing standardized maintenance procedures by automatically documenting system failures, supporting decision-making, and guiding the operator by giving maintenance instructions with 3D visualizations, images, text, and videos [22][23].

AR troubleshooting, especially in real-time maintenance scenarios with relevant data (detailed, high-resolution images and 3D models, and real-time sensor information) and maintenance activity tracking, may benefit from robust processing power. These specific requirements can vary based on the nature of the application and the devices involved. For effective usage of resources, interconnections of AI/AR, and maintenance content, a centralized data platform is required for content filtering and distribution to the AR systems [24]. Not only the technological perspective is considered, but improving human-machine interaction through real-time AR instruction exchanges across the maintenance procedures is accounted for in this research.

1.3 Industrial context

Besides the scientific relevance of contributing to the academic discussion in the research, this dissertation also aims to provide results that can be applied to support the work of maintenance operators. This section, therefore, introduces the industrial context background of NS, the company that has sponsored the research project described in this dissertation.

NS is a railway company responsible for rail transport on the Dutch main rail network and has several units including NS Operations, Commerce & Development, NS Stations, HR, Finance, and IT (32.000 staff on average in 2022) [25]. Since 1937, NS has contributed to mobility and progress in the Netherlands. NS has pursued a cost-savings program worth €1.4 billion since 2020 while continuing to invest on behalf of the passengers. In 2022, NS made substantial investments in modern intercity trains to accommodate the anticipated growth in passenger numbers and invested in digitalization and innovations. Furthermore, in the same year, NS temporarily withdrew an average of 17.3 % of its rolling stock for maintenance, repairs, and refurbishment. NS is finding it necessary to withdraw rolling stock more frequently due to defects and related logistical challenges. Figure 1.1 provides an overview of the rail network operated by NS and the inventory of owned rolling stock.

Rolling stock type (Sprinters)	Number of rolling stock
SLT	131
SNG	205
Flirt (excl. TAG)	58
Rolling stock type (Intercity)	**Number of rolling stock**
ICRmh (Traxx)	131
VIRM	176
ICM	103
ICNG	99
DDZ	49
Rolling stock type (International)	**Number of rolling stock**
Eurostar	2
IC Berlin	76 (15 e-locs)
ICE	3

Figure 1.1. The rail network used by NS and rolling stock inventory in 2023 [25].

1.3.1. Organizational motivation

To remain relevant in Dutch society, NS is working to optimize its performance both on aspects that are important today and on demands that will be made of NS in the future. As NS is innovating, major challenges such as implementing timetable adjustments, improving performance, facilitating the energy transition, and dealing with labour shortages are faced. According to RepTrak, NS scored 54.2 (on a scale of 1-100) as an innovative company in 2022 [26], the median RepTrak score is 62.9 for organizations. To maximize innovative impact, NS collaborates with many actors, including research institutions as well as other players in the railway sector, and start-ups. NS permanently evaluates the opportunities offered by six relevant technological developments: AI, 3D printing, 5G connectivity, sensors, AR/VR, and process mining [27]. Below are examples of major innovations that contribute to the strategic themes of NS related to maintenance and AR [25]:

- Developing a new decision-support system for effectively responding to constantly changing maintenance and operational circumstances by incorporating the current logistical situation, scheduled and unscheduled train maintenance, and the expected number of passengers.

- Maintenance inspections by using image recognition for inspections of pantographs and wheelsets. The high-resolution images and the possibility to zoom in on specific components increase the quality of inspections.
- AI support to improve passenger forecasts, recognize graffiti, enhance the rolling stock scheduling system and personalise marketing activities.
- Exploring the use of AR for maintenance support by deploying remote support and giving remote instructions.
- Data collection (images, temperature, vibrations, etc.) by sensors in trains, tracks, workshops, and stations for safe rolling stock deployment, preventing unscheduled outages, and monitoring real-time rolling stock data.

In practice, however, the application of AR for rolling stock maintenance faces challenges, such as data availability, (human) resources, and experience with AR technologies. Besides this, legal and regulatory constraints are critical at the organizational level when it comes to implementing AR in maintenance. The long-term incentive of NS is looking for pragmatic ways to support operators in AR decision-making and troubleshooting IT/OT system failures.

This research contributes to an approach wherein the railway industry advances the development and testing of AR measures to troubleshoot at the convergence of IT/OT interfaces, rolling stock, humans, and processes. It contributes to decision-making and implementation of measures at these interfaces. This research is not bound to specific asset technologies or domains.

1.4 Research motivation

This research focuses on the design, creation, and development of AR for troubleshooting and maintaining IT/OT rolling stock systems and proposes both technological and nontechnological artefacts to improve maintenance practices and facilitate the integration of AR tools and services into existing operations. This section focuses on the research motivation by including a state-of-the-art and the research gap.

1.4.1. State-of-the-art

Industry 4.0 terminology originated in Germany and was part of the high-tech strategy for the future of German manufacturing. The concepts of Industry 4.0 have gained global recognition and have been embraced in various countries as a framework for modernizing and advancing their industrial sectors. AR-based research is conducted globally in various countries, reflecting a widespread interest in leveraging AR technologies across different industries. The synergy between AR and Industry 4.0 reflects a global effort to leverage advanced technologies for the transformation of manufacturing and industrial processes.

The literature review in this research is guided by a thematic framework that focuses on the intersection of maintenance and AR within industrial engineering domains.

A systematic search strategy was employed to gather relevant journal and conference articles. To support the motivation of this research through literature, a total of 390 journal and conference articles containing keywords such as “maintenance” and “augmented reality” were collected. This targeted approach ensures that the collected literature directly addresses the specific context of the research, allowing for a more focused and comprehensive review of relevant studies. By using keywords like “maintenance” and “augmented reality”, the research narrows its focus to a specific intersection of topics, which is advantageous in ensuring that the collected literature directly addresses the intended research context. The thematic distribution of the collected publications, as illustrated in Figure 1.2, highlights key areas of interest and indicates promising avenues for further exploration within the field of industrial engineering. By utilizing this thematic framework, the literature review aims to provide a structured analysis of existing research, identify gaps or trends, and contribute to theoretical advancements in the application of AR in maintenance practices.

The red line in the cumulative percentage graph represents a critical threshold, indicating the point at which a significant proportion of the literature converges on key themes. Notably, Figure 1.2 reveals promising avenues for further research within industrial engineering domains.

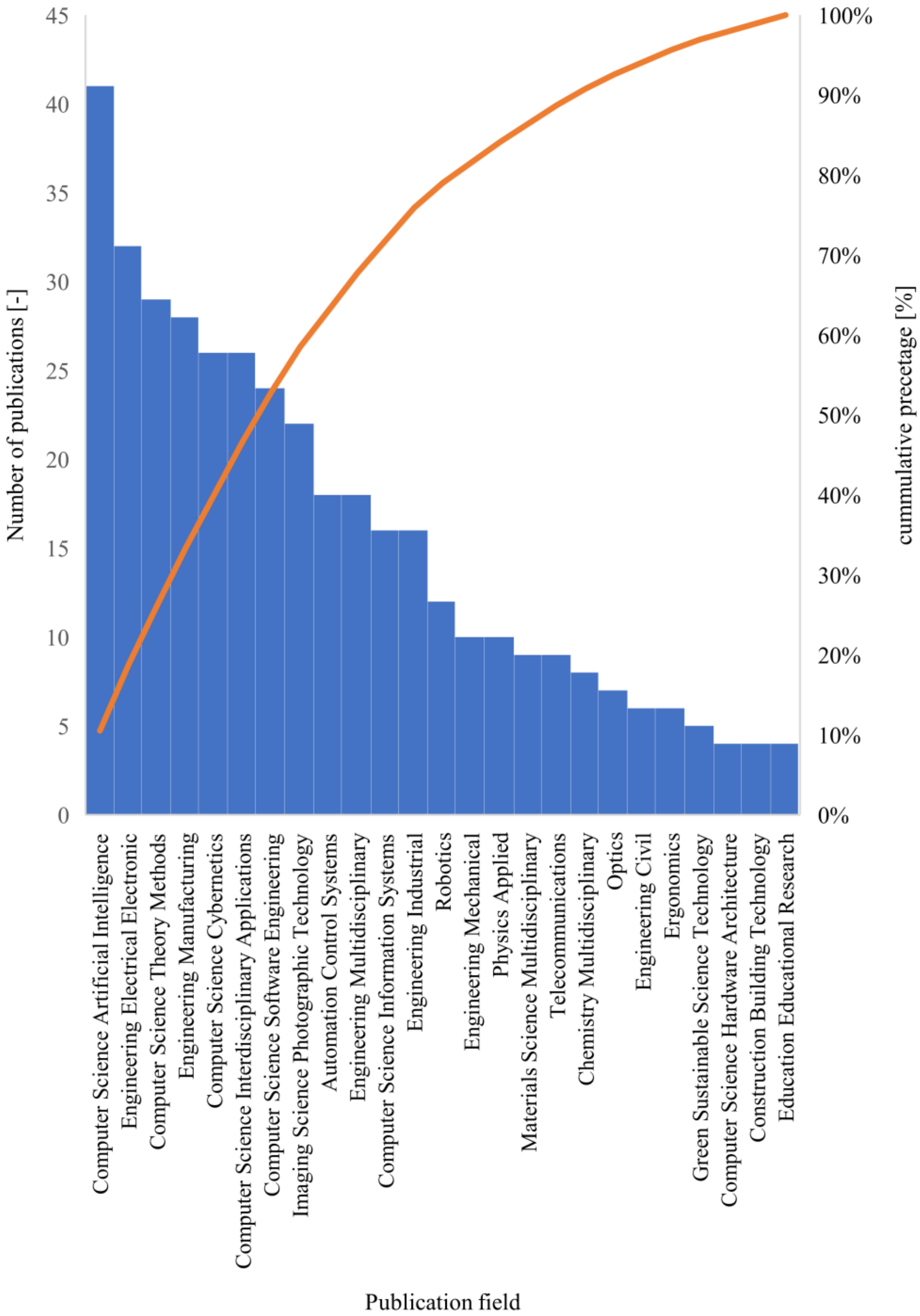

Figure 1.2. Publications in journal and conference articles of AR in maintenance context.

In reviewing 390 journal and conference articles on maintenance and AR concepts, the analysis reveals a common categorization of research topics into three levels: macro, meso, and micro [28]. The macro-level involves a broad examination of overarching societal or system factors. Meso-level analysis in AR troubleshooting refers to an intermediate middle scale of analysis studying team dynamics, collaboration, and communication in maintenance teams or functional units. Examples of meso-level topics include studying the effectiveness of collaboration tools in maintenance teams or analysing communication patterns during troubleshooting sessions.

On the other hand, micro-level analysis in AR troubleshooting refers to the analysis of individual components, actions, or entities within a system by representing a smaller scale of examination. This level of analysis may include investigating the usability of specific AR interfaces for maintenance tasks, assessing the accuracy of AR-based diagnostic algorithms, or examining the impact of individual operator behaviours on troubleshooting outcomes. For this research, the decision has been made to exclude the macro-level. This decision stems from the specific focus of the study on the intricacies of AR implementation within the railway sector, specifically delving into operational and organizational dynamics. The exclusion of the macro-level allows for a more focused exploration of the meso and micro-levels, ensuring a detailed and targeted analysis tailored to the specific context of the railway industry.

Combining meso and micro-level explorations provides a comprehensive understanding of how AR is implemented and experienced both at organizational and functional levels and by individual components and end-users [29]. In addition, insights from both levels contribute to the development of holistic solutions that address functional, organizational, and technological needs in the maintenance domain. Figure 1.3 presents the research fields and research topics on meso and micro-level. Meso-level AR troubleshooting in the maintenance domain includes topics in the fields of Human-Computer Interaction, Design & Manufacturing, and Computer Vision & Graphics. Micro-level exploration of AR in maintenance reveals topics revolving around the AR technology itself, Industry 4.0 concepts, and Project Scheduling. Resulting from the meso and micro-level analysis, this research covers the topics in the field of Human-Computer Interaction, Design, Organizational impact & Management, Fault Diagnosis, Decision-making, AI, and Maintenance.

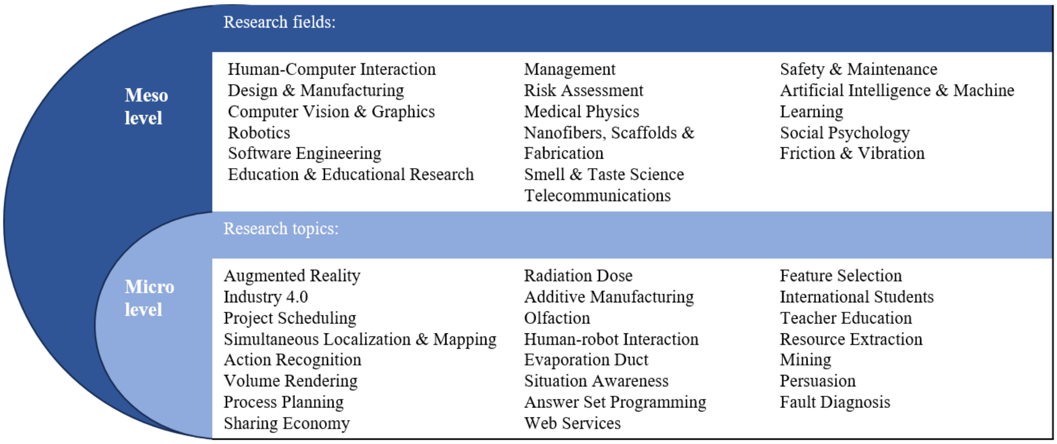

Figure 1.3. Meso research fields and micro research topics.

1.4.2. Research gap

The accuracy and efficiency of maintenance and troubleshooting of complex systems are increasingly challenged by (1) data overload, e.g. difficulty in extracting meaningful information, (2) variety of data sources, e.g. sensor data, logs, performance metrics, (3) system interdependencies, e.g. difficulty of root cause identification, (4) real-time data challenges, e.g. analysing and acting upon data in real-time necessitates advanced tools and strategies, and (5) complex algorithms and models for troubleshooting, e.g. understanding, implementing, and fine-tuning maintenance and troubleshooting procedures and failure analysis may contribute to the complexity of maintenance tasks [1][3]. Digitization can empower maintenance services by making use of collected data to monitor the equipment's health, diagnose faults, and predict and troubleshoot failures well before they happen. The adoption of AR in various industries is anticipated to be a significant trend in the coming years, with widespread recognition of its importance by both industries and academia [30]. AR is likely to play a crucial role in advancing of troubleshooting IT/OT rolling stock failures, offering valuable support to operators by providing rolling stock system failure information and maintenance guidance. However, despite its anticipated significance, there is a notable gap in leveraging AR for troubleshooting IT/OT rolling stock failures.

This research supports the further development of AR to address the increasing IT/OT complexity of rolling stock and provide maintenance guidance, by integrating ML and a centralized data platform to help in the analysis of the collected maintenance and failure data sets to automatically diagnose the rolling stock health state, perform inspections, and predict failures. Human operators and decision-makers must be in the loop and capable of interpreting results as the AR troubleshooting system can fail. To address the troubleshooting and maintenance of IT/OT system failures, this research contributes to the development of an innovative method based on integrated AR, information systems and system principles, and maintenance concepts.

1.5 Research goal and research questions

This thesis aims to explore how AR contributes to troubleshooting and maintaining IT/OT converged systems faced by the railway industry. This study investigates the applicability of the technology by different case studies. The Main RQ is cast in the form of a 'how' question. This type of question requires an answer that describes how the maintenance strategies should be, instead of what the maintenance strategies are currently like. As discussed in section 1.2 of the introduction, this research has combined practical and theoretical contributions.

Main RQ.	How to use AR to support operators in troubleshooting and maintaining IT/OT converged rolling stock systems faced by the railway industry?
subRQ1.	What are the current state, research challenges, and future directions for using AR for IT/OT failures in the maintenance operations of digitized trains?
subRQ2.	How to incorporate the operator's perspective for AR troubleshooting and support the decision-making procedures in maintenance operations?
subRQ3.	What criteria govern AR to collect, structure, predict, and troubleshoot IT/OT failures by combining CSP, AI, and case-based reasoning?
subRQ4.	What design and functionality specifications ensure the interaction in AR to troubleshoot rolling stock system failures and enhance human-AR maintenance procedures?
subRQ5.	What organizational obstacles, requirements, and viewpoints do stakeholders have concerning the implementation of AR in railway organizations?

The research outcome is expected to be generalizable to other domains in which complex IT/OT convergence is managed. Similarly, the scalability of the research is defined here as the opportunity to be applied in the context with different characteristics in terms of dimensions, demands, or systems.

1.6 Methodology

To achieve this goal and answer the RQs a mixed-method pragmatic approach is adopted that combines both qualitative and quantitative data collection techniques and analysis procedures [31]. Following this approach, the research starts with a contextual review to conduct a thorough literature review, defining and conceptualizing the purpose of the study. This involves synthesizing existing knowledge and identifying gaps in the literature that the study aims to address. By grounding the research in existing theory and empirical evidence, this phase provides a foundation for subsequent methodological decisions. Subsequently, a case study analysis ensues, encompassing the selection of an appropriate methodology, the definition of procedures, and the choice of a representative case study, which includes participant and industrial application selection. The case study approach allows for an in-depth examination of the phenomenon of interest, providing insights into its complexities and nuances. The focal point of the design output phase is the execution of the selected case study design, involving the creation and evaluation of artefacts or interventions that directly address the RQs. This phase involves collecting both qualitative and quantitative data through various methods such as observations, interviews, surveys, or experimental procedures. By systematically collecting and analysing data, findings can be interpreted and conclusions can be drawn that address the RQs. This mixed-method pragmatic approach guarantees a systematic and thorough examination of the research goal by associating each subRQs with a distinct phase within the research process.

The adopted methodology of the research is briefly discussed for each RQ and placed in the context of the AR troubleshooting context.

Main RQ. In addressing the question of how AR can support operators in troubleshooting IT/OT converged rolling stock systems in the railway industry, a comprehensive research methodology employing a mixed-method pragmatic approach is essential. This multi-method framework emphasizes the integration of qualitative and quantitative techniques to provide a nuanced understanding of the phenomenon under investigation. Utilizing this approach, the research begins with a contextual review, delving into existing literature to grasp the complexities and challenges inherent in rolling stock maintenance. A case study analysis enables the selection of an appropriate methodology and the identification of representative case studies for in-depth exploration. Additionally, techniques such as ethnography, involving the observation of AR applications in real-world contexts, are integrated seamlessly into the research framework to provide rich insights into operator experiences and challenges. The data collected, including interviews and observational data, undergoes rigorous analysis involving a systematic coding process from inception to completion. Data familiarization supports understanding of the content and context of collected data, which is followed by initial coding and open coding. These coding techniques offer flexibility and creativity in capturing the richness and diversity present within the data. Theme identification, data reduction and interpretation facilitate the analysis of relationships between themes, exploration of connections with existing literature, and the formulation of conclusions based on the findings. Throughout the research process, experts in the field are included to validate the decisions to ensure the reliability and credibility of the process.

subRQ1. To investigate the current state, research challenges, and future directions for using AR for IT/OT failures are considered the prominent drivers for troubleshooting. The initial stakeholder needs and desires were gathered through interviews with various stakeholders in the railway industry. Through semi-structured interviews and a literature review, the researcher can obtain an in-depth understanding of the stakeholder's needs and desires, which are coded, categorized into themes, and analysed to extract meaningful insights. A qualitative field study supports the initial root cause examination by providing a more detailed data analysis of the current troubleshooting methodology. The field study supports the motivation of the research by underpinning the complexity of IT/OT troubleshooting and is used for further investigation of AR support tools.

subRQ2. Based on the stakeholder needs and desires, research challenges, and future directions elicited in subRQ1, operator objectives for AR troubleshooting were formulated. To evaluate the applicability and accessibility of an AR troubleshooting tool, an adaptive architectural framework aimed at shaping and structuring the process that provides operators with tailored support is proposed. The adaptive architectural framework is supported by literature foundations. In addition, based on semi-structured interviews for data collection, an AR decision-making support tool based on structuring, visualizing, and contextualizing data is developed. Design Science Research (DSR) is deployed to design a decision-making tool in a laboratory setting. A case study identifies the technology adaption patterns and defines the requirements needed to support the operator.

subRQ3. After considering the operator’s perspective and AR decision-making process requirements, as mentioned in subRQ2, the data handling, data architecture, data processing methods, database structure, and troubleshooting characteristics exploration and identification are key. To provide the operator with real-time access to fast-flowing data, a hybrid solution is recommended, combining AR with ML software. This solution introduces a dynamic reference map of all required modules and relations that connect ML with AR. Data collection is performed by literature review and semi-structured interviews with key stakeholders. Furthermore, an AR database architecture is developed to discover maintenance patterns and provide troubleshooting directions by pre-processing data using ML data mining tools. A case study in an industrial setting of adaptive fault detection for immediate validation was exploited. Cross-validation techniques identify challenges and opportunities related to the AR database architecture.

subRQ4. The functionality and effectiveness of an AR troubleshooting tool should be determined to resolve IT/OT rolling stock system failures. The hybrid solution made of AR must be connected to a centralized database platform for real-time data streaming (subRQ3). The functional building blocks for AR troubleshooting are proposed, based on DSR, together with the AR design guidelines to highlight the importance of the functional requirements, including the operator perspective (subRQ2), and develop an intuitive UI experience. Following a human-centred design approach, DSR prototyping in an industrial setting is used to iteratively develop an AR troubleshooting tool. The input and feedback of stakeholders are used to gain further understanding of the stakeholder needs and desires as well as to determine refinements and new directions for the troubleshooting tool. Moreover, to facilitate participatory design research, all stakeholders must be able to identify and work with the AR troubleshooting tool. A case study in both laboratory and industrial settings was performed. For immediate prototype validation, the study, therefore, focused on (1) how the functionality fulfils the needs of expert operators, and (2) how the UI can support troubleshooting.

subRQ5. The impact of AR on railway organizations is assessed, aligning with stakeholder needs, AR requirements (subRQ1 and subRQ2), and design objectives (subRQ3 and subRQ4). To investigate the current readiness and maturity of AR in railway organizations a semi-structured interview is deployed supported with questionnaires. In addition, the readiness and maturity assessment with Interpretive Structural Modelling (ISM) are combined to measure the organizational AR implementation and adoption requirements. Based on the interviews, questionnaires, and aforementioned combined research methods, an organizational AR roadmap was designed and verified using a case study together with experts from the railway organization.

1.7 Reading guide

To join the scientific debate about the research outcome as early as possible, publications are disseminated at various stages throughout the PhD trajectory. During the PhD journey, a publication strategy was adopted that aimed at publishing and presenting the core findings of the research in academia using peer-reviewed conference proceedings and journal publications. As a result of this approach, the dissertation consists of a collection of individual publications.

Together with the introduction and the conclusion, these publications form the main structure of the dissertation, resulting in a total of ten chapters. Chapters 2-9 are intended for publication and can therefore be read as standalone pieces of the thesis. A summary of the content is given at the start of each chapter in the form of an abstract. Each chapter is divided into sections. Throughout the dissertation, references to sections that do not specifically mention a chapter number will refer to sections within the same chapter. The research is divided into five distinct themes, with each subRQ corresponding to a specific theme, as illustrated in Figure 1.4.

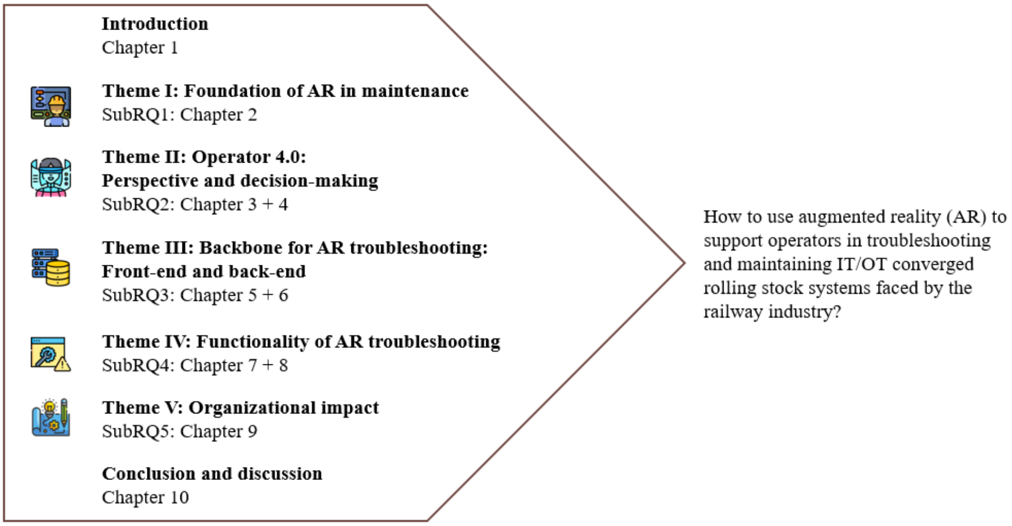

Figure 1.4. An overview of the research structure.

1.7.1. Theme I: Foundation of AR in maintenance

The first theme is focused on positioning the research and establishing a research foundation. It contains one chapter that contributes to developing the main artefact of this dissertation.

Chapter 2 – Augmented reality for IT/OT failures in maintenance operations of digitized trains: current status, research challenges and future directions

This chapter explores the research foundation by presenting limitations and challenges in troubleshooting IT/OT failures using AR. Based on current rolling stock maintenance operations, potential AR solutions and specifications are discussed. Moreover, this chapter reveals the potential AR application fields for rolling stock maintenance.

1.7.2. Theme II: Operator 4.0: perspective & decision-making

Not only is the AR technology the focus of this thesis, but the operator role is of great importance as well. The second theme therefore revolves around the operator perspective (Chapter 3) and the decision-making process that plays a role in this (Chapter 4).

Chapter 3 – How to make augmented reality a tool for railway maintenance operations: Operator 4.0 perspective

The third chapter presents an adaptive architectural framework for a structured procedure enabling a systematic approach for tailored-based support using AR. This research fulfils the need for operators to supply them with customized and contextualized maintenance support by combining complex methodologies with high AR usability requirements. The study deploys a human-centred approach for the successful adoption of AR technology tools in the railway industry.

Chapter 4 – Supporting maintenance operators using augmented reality decision-making: visualize, guide, decide & track

Chapter 4 describes the developed AR decision-making tool based on structuring, visualizing, and contextualizing data in an AR solution space. The tool uses object recognition for visualizing maintenance instructions, performs a what-if analysis for troubleshooting directions, and captures maintenance time and activities performed. This study takes into account the limitations set by operators in troubleshooting activities (Chapter 3).

1.7.3. Theme III: Backbone for AR troubleshooting: Front-end & back-end

Compared to the first two themes, the third theme assumes a more AI-fundamental approach, with a focus on connecting AR and AI. Chapter 5 gives a holistic view of integrating computational systems for automatically classifying and identifying system failures with AR assistance, and directly impacts an organization's data infrastructure and management. Identifying data processing techniques and developing a centralizing information management information is required, hence Chapter 6.

Chapter 5 – Troubleshooting: a dynamic solution for achieving reliable fault detection by combining augmented reality and machine learning

A dynamic reference map of all modules required to perform automatic fault diagnosis is presented in Chapter 5. The reference map describes the connection between KBS, AR, and AI in existing maintenance systems. The study focuses on image classification and performing maintenance on a physical component.

Chapter 6 – Augmented reality database architecture: the backbone for IT/OT rolling stock maintenance

The key features in this chapter include developing an AR database architecture featuring data handling and fault diagnosing via AR, allowing entities in the platform to create a hybrid fault diagnosis model to discover maintenance patterns, recognize the health status of the rolling stock, troubleshoot IT/OT failures, and visualize the maintenance information. Both manual data processing and Natural Language Processing (NLP) techniques are used to filter, categorize, and process data. Scientific, organizational, and technological perspectives are highlighted to understand and justify the importance of an AR database architecture.

1.7.4. Theme IV: Functionality of AR troubleshooting

Integrating real-time maintenance information with existing fault-diagnosing strategies while having tailored-based information in the UI is key for effective human-AR collaboration. This research theme combines both functionality and UI requirements to collectively contribute to AR troubleshooting.

Chapter 7 – Using functional blocks for rolling stock troubleshooting: sequential augmented reality assistant (SARA)

Chapter 7 proposes posing functionality building blocks for troubleshooting IT/OT system failures. The main functionality requirements for AR troubleshooting consist of cloud-based data fusion and analytics, NLP understanding, maintenance prediction models, AR assistance and visualization, and information exchange and feedback. A Sequential AR Assistant (SARA) troubleshooting prototype is developed reflecting upon the AR functionality building blocks in an industrial environment.

Chapter 8 – Developing AR design guidelines for troubleshooting rolling stock system failures: Industrial prototyping and human factors

AR troubleshooting is part of the human-centred-multi experience requiring tailored-based UI information support. Chapter 8 presents AR design guidelines aimed at converging the AR technology with the human-centred fault-diagnosing domain. Functional and UI experience requirements are presented utilizing operator input. A railway case study is used to develop prototypes iteratively and shows how the AR design guidelines support operators in structuring and contextualizing data and decision-making strategies.

1.7.5. Theme V: Organizational impact

The final theme assumes a pragmatic approach by recognizing the interconnectedness between AR-based troubleshooting research and AR adoption in railway organizations. In this theme, the readiness and maturity of AR in railway organizations are assessed and combined with ISM. Both methods support the translation of the conducted research into a practically applicable AR roadmap.

Chapter 9 – An augmented reality roadmap for rolling stock organizations

Organizations are facing substantial challenges in implementing and adopting AR in their business model. Chapter 9 combines a maturity and readiness model with ISM that reveals its applicability in railway organizations and forms a foundation for an AR organizational roadmap.

1.7.6. Conclusion and discussion

Chapter 10 offers a conclusive overview of the research objectives, addressing the Main RQ, along with the subRQs that underpin the core findings. Additionally, it outlines various limitations encountered during the research process. Furthermore, the chapter delves into prospective areas of exploration related to the capabilities of AR technology, the technical artefacts involved, and potential applications in other industrial contexts.

Chapter 2 – Augmented reality for IT/OT failures in maintenance operations of digitized rolling stock: current status, research challenges and future directions

Publication history: This chapter is published by the 31st CIRP design Conference 2021 (CIRP Design 2021). https://doi.org/10.1016/j.procir.2021.05.038

Changes: This chapter is translated from United States to British English and the terminology of train(s) is replaced by rolling stock

2.1 Theme I: Foundation of AR in maintenance

Chapter 2 strategically positions this research in the railway industry's digital transformation, emphasizing challenges in IT with OT convergence within digitized rolling stock (Figure 2.1).

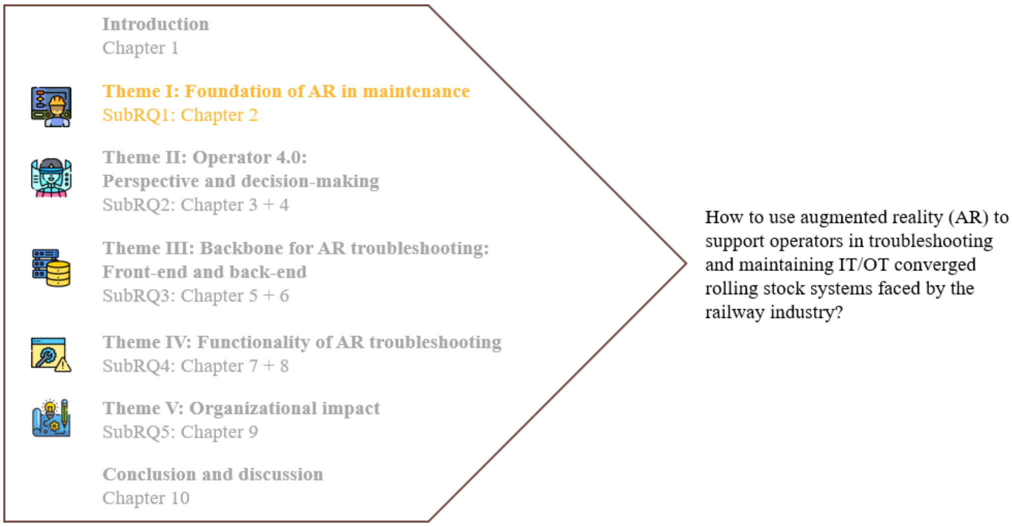

Figure 2.1. Theme I: Foundation of AR in maintenance.

The railway industry is moving towards a complex socio-technological system that relies on computer control and human-machine interfaces. Digitization and convergence of IT with OT becomes increasingly important. Therefore, enabling innovations, lowering costs, increasing safety systems, enhancing performance, and increasing flexibility gains. In this scenario, opportunities arise for AR capabilities to enhance maintenance operations of digitized rolling stock. Initial research and tests have enabled training technicians and assistance of rolling stock drivers during specific activities by facilitating interactions with machines that go beyond traditional training manuals. Despite the positive results AR has shown, there are no specific indications available regarding the 'deployability' of the technology related to maintenance tasks. This position chapter presents arguable boundaries and challenges for a structural appraisal of AR on maintenance operations of IT/OT converged rolling stock. Potential AR solutions and specifications were based on current maintenance operations. Semi-structured interviews and surveys were conducted with maintenance providers to determine existing challenges. Moreover, the chapter comprises an analysis to reveal the potential application AR has in the maintenance procedures of digitized rolling stock. Finally, this chapter provides future research directions of AR technologies related to maintenance procedures of rolling stock.

2.2 Introduction

Over the last few years, the railway industry has experienced a tidal wave of digital transformation whose impact is complex. This industry is a socio-technical system that is becoming increasingly concerned with digitization. Key performance indicators (KPIs) for railway operations remain the same, but each of them will show a positive impact from the application of digital technologies. Technological innovations in rolling stock and traffic management systems create new services and commercial business cases [32]. Overall competitiveness and performance improve by exploiting data-based services with for example: AI techniques, merging real and virtual worlds, autonomous driving, the IoT, and blockchains that innovate the railway system. The railway industry aims to have safe, high-quality, and sustainable transport and maintenance operations. Maintenance costs depict a significant proportion of the life-cycle costs of rolling stock, where fleet maintenance costs significantly exceed the initial investment costs. A fundamental part of supporting rolling stock throughout the entire life-cycle of a rolling stock is therefore maintenance.

Digitization and convergence of IT with OT have become increasingly important for railway operations to achieve less maintenance cost and efficient, and reliable operations. Here, IT is defined as an engine that accepts data flow as an input to deliver new data flow but does not interfere with the physical world [33]. OT is a set of devices and processes that act in real-time on physical operational systems. Because of digitization in the railway industry, maintenance of new rolling stock is more often focused on (remote) inspections based on data rather than on physical assembling and disassembling components. An additional result of digitization is more IT and OT systems are implemented into rolling stock. IT/OT convergence lowers costs, reduces risks, enhances rolling stock performance, and reaches flexibility gains [33]. Convergence generates more data, data relationships, and dependencies, thereby requiring early identification of critical interfaces. However, the convergence of IT/OT is highly complex due to the involvement of different independent systems, technologies, stakeholders, equipment, and methods [34]. Finally, failure within the boundaries of IT/OT converged systems is thereby largely unpredictable and increasingly involute.

Based on a case study, it was found that failures are not yet fully understood by today's asset and fleet managers. In addition, knowledge of IT is limited and only present in a few departments. Furthermore, the collaboration between IT and maintenance departments lacks coherence. As a result, only a few employees have competence in both IT and OT of the rolling stock, creating an IT/OT failure knowledge gap. Therefore, understanding and structuring IT/OT systems is of great importance for the railway industry. To meet this interest, this research aims to examine the use of AR as a tool for identifying, prioritizing, and providing solutions to failures related to IT/OT converged systems. AR is capable of showing the right information in the right context to support users in finding this malfunction [35]. AR is a technology, mature enough to be widely deployed in maintenance operations, testing, and training of converged IT and OT rolling stock. However, challenges of deployability and integration of the technology must be dealt with. An overview of this position chapter is presented in Figure 2.2.

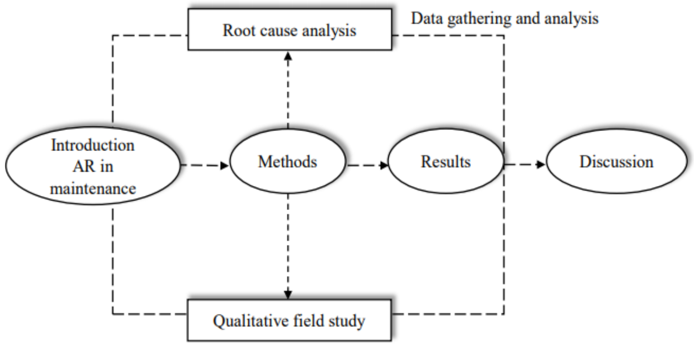

Figure 2.2. Position chapter outline.

This research investigates the use of AR as a tool mainly for IT/OT failure analysis. Failure analysis is a method used in product development to determine weaknesses and technical risks. As a result, it optimizes the use of resources. Identification, prioritizing, and structuring of IT/OT failures enables designers to perform failure analysis during the conceptual design. This analysis through AR is recognized as a powerful tool to improve quality and reliability during product development.

2.3 AR status in maintenance operations

When assessing the current AR status in maintenance operations, a brief specification of AR application fields is required. A clear AR tool description helps to understand the technology which will be used in this research. System boundaries are presented next to evaluate the current technology implementation status. All information results in positioning AR tools in different maintenance fields.

2.2.1. Specification of AR technology

AR techniques can be used to visualize contextualized virtual information at the appropriate time and location within the working environment. Potential applications of AR in industrial ecosystems are primarily focused on maintenance, service, inspection, device diagnostics, repair of complex machinery, and training [36]. Easier understandable instructions are provided as computer-generated information superimposed upon the actual equipment and step-by-step explanations of tasks. A report on mechanics' capability of viewing virtual information panels that overly the real image of engines and see through the machinery without disassembling components was already proposed in 1993 [37].

Typical AR systems include components such as visualization/capturing devices, interaction devices, and tracking systems [37]. Capturing technologies collect environmental data and can be viewed by the user with superimposed information.

Visualization devices are used to display the results of image processing. Interaction devices are used for commands that affect information processing and displaying. Tracking technologies are essential for identifying user position and providing correct information when augmenting the environmental scene itself. Technical and technological issues related to the development and implementation of AR are debatable elements. Most studies that review technological solutions for visualization either use mobile devices or Head-Mounted Displays (HMDs) [38]. Mobile devices need to be held in the hand when used and therefore potentially hinder maintenance tasks. HMD solutions leave the hand free, allowing for a more natural and intuitive hand-based interaction with virtual objects. Two main categories of tracking systems can be defined: marker-based tracking and marker-less tracking [39]. Marker-based solutions use tags placed on elements that let the AR system recognize them and allow it to convey additional information. Marker-less systems are for example hybrid tracking methods, feature tracking or natural markers. Nowadays, marker-less AR is the preferred image recognition method depending on the environment's real features rather than identifying markers. This method eliminates the need for object-tracking systems. Marker-less systems require computer-aided design (CAD) models, 3D point clouds, or plane segments. Therefore, a complete and accurate data structure is essential.

2.2.2. Prior research AR in maintenance

A case study in aircraft maintenance training and operations support suggests that AR technology can improve maintenance task efficiency [40]. The production environment also provides multiple cases in which AR performs like a work support system in a challenging and complex environment [41]. All cases demonstrate positive results regarding AR and complex maintenance procedures in terms of efficient, reliable, and safe operations.

2.2.3. Current status of application AR in the railway industry

Previous research has been conducted within the railway industry for adopting AR technologies to train technicians and assist rolling stock drivers during specific operations [42]. A proof of concept was proposed by targeting the main advantages: increasing operational efficiency and training. Despite the positive results AR can achieve, several questions remain unanswered regarding the deployability of these emergent solutions.

2.4 Methodology

To examine whether AR can be a suitable tool for identifying, prioritizing, and providing solutions to failures related to IT/OT converged systems, a case study is performed for NS. A qualitative field study is used to support the initial root cause examination by providing a more detailed data analysis of the current situation. This field study supports the motivation of the research by verifying whether the failure of complex IT/OT systems can be detected and further investigated by using AR tools.

2.4.1. Characteristics interviewees

Participants of this field study were employees of NS. The majority of the group was within the department of NS-technology. Participants were selected based on their knowledge of IT/OT convergence, data collection and management, innovative technology and maintenance operations knowledge. In total, 28 individuals were selected for interviews representing 35% of the total sample size. This sample size is sufficient within this specific field of knowledge to generate correct information [43]. Table 2.1 shows the field of expertise of the interviewees, some experts knew multiple fields.

Table 2.1. Expertise knowledge.

Focus area	**Number of experts**
IT/OT convergence	14
Data collection and management	8
Innovative technology	3
Maintenance operations	24

2.4.2. Field study procedure

The dataset was gathered by using a combination of theoretical sampling and purposive sampling. This results in a process of data collection whereby codes are collected and data are analysed. Based on the analysis, theories can be generated. Interviews were held online in times of Covid-19. Online platforms are suitable for qualitative research to conduct individual interviews as well as small focus groups. Participants were informed about the topic of interest before the interview. Each interview was scheduled to take approximately one hour. Semi-structured interviews were used to allow specifying initial questions, if necessary existing questions were specified or innovative questions were proposed to be more precise. During the interview, analytic notes were made. A summary of the interview was shared and discussed with the participants to verify the outcome.

2.4.3. Field study analysis

Qualitative data was analysed by performing theoretical latent analysis [44]. Six steps are required to process data from the interviews: (1) familiarize with data, (2) generate initial codes, (3) search for latent themes, (4) review themes (5) define and name themes, and (6) produce reports. To systematically analyse complex phenomena hidden in the unstructured data, ATLAS.ti is used [45]. The analysis was based on open coding procedures in which codes are not pre-set but developed and modified during the coding process. Quotes of interviewees were assessed and many potential themes were generated for coding. After scoping the content of each theme, thematic analysis can be performed. Throughout the entire study, a constant comparative analysis is performed to find consistencies and differences enabling refinement of the concepts.

2.5 Root cause analysis through the Ishikawa diagram

Preliminary analysis of utilizing AR technologies within maintenance procedures of NS revealed multiple complex and interdependent problems. Understanding, structuring, and prioritizing problems allows obtaining clear and transparent problem identification. A widely used method in the rail transport sector is RCA by recognises the problem in a structured way. Different problem sources are distinguished and all directly cause an overall effect on identifying IT/OT convergence failures. Quick identification of root cause problems in NS can be achieved by using the causal diagram of Ishikawa, one of the multiple options for performing an RCA. This tool is a suitable instrument for problem-solving methodologies and not only for the analysis of quality characteristics. Recognizing root cause problems enables companies to implement focused and specific improvement actions [46]. The Ishikawa diagram for finding proper tools to identify, structure, and solve IT/OT problems in the current maintenance procedure of NS is presented in Figure 2.3. The diagram is based on interviews and documents collected from NS. Firstly, the factors that affect the utilization of AR technologies are specified. The cause of the failure leads to different failure sources. Secondly, failure causes are grouped into major categories to identify and classify these failure sources. Thirdly, the root causes of the problem can be specified. Lastly, the company can address root causes by allowing specific improvement actions.

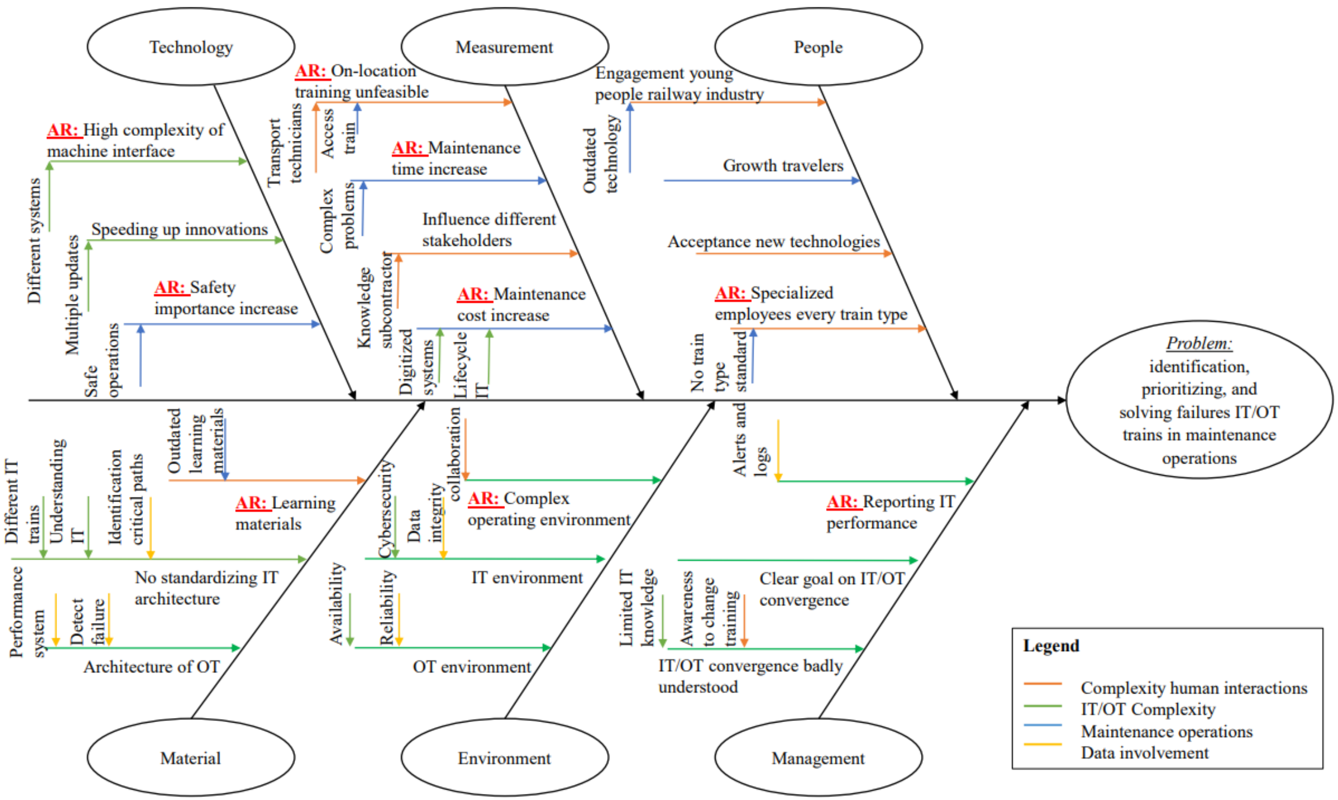

Figure 2.3. RCA using the Ishikawa diagram.

2.6 Field study results

Participants were questioned about four main topics: IT/OT convergence, data gathering and management, transition maintenance procedure, and AR potential application fields.

2.6.1. Qualitative analysis results

From the interview results, 44 codes were generated. The codes were divided into 8 themes. Table 2.2 represents examples of how quotes were categorized and form a theme.

Table 2.2 Quote, category and theme division.

Quote	Code	Theme
AR can be performed on the revision of components, brake cylinders, bearings and low-voltage installations.	AR for support maintenance work	Potential applications for AR
Sensitive data needs to be protected at all times	Data related to complex problems	Data complexity
Preventive maintenance of IT/OT systems is in the development phase and is currently only used for high-risk cyber-security operations	Comparison of maintenance procedures	Maintenance procedures
IT/OT convergence is difficult due to the complexity of the systems, involving different technologies, employees, equipment and methods	IT/OT complexity	IT/OT failure
A continuous connection between shore and operation is required but not always established	Connection failure	Failure causes
It becomes possible to predict when a failure occurs using data	The future potential of data	Future steps

2.6.2. IT/OT convergence

Unsurprisingly, 17 individuals are experiencing difficulties with IT/OT convergence. The interviewees mentioned that the convergence of IT and OT systems is becoming more important in the next decade. IT/OT convergence failure is mostly caused by new or incompatible IT systems, software bugs, connection failure, and complex configuration management. Table 2.3 presents the most occurring failure causes of IT/OT systems. IT/OT complexity represents 41% of all failure causes.

Table 2.3. Most occurring failures are caused by digitized rolling stock in NS.

Failure type	**Number of times mentioned by interviewee [%]**
Connection failure	15.9
IT/OT complexity	41.3
Mechanical failure	11.1
Software bug	20.6
Configuration management	11.1

Participants did recognize the importance of digitization, citing benefits such as increased reliability and operability of rolling stock, less downtime, less maintenance cost, and on-time travelling. Other often mentioned topics were about the importance of cybersecurity in which confidential data needs to be protected from cyber-attacks or data leakage.

2.6.3. Data gathering and management

The results of the field study revealed that data gathering and usage were both considered to be highly complex tasks. Digitized rolling stock generates a lot of data; this large amount of data is stored and protected. Different data types can be distinguished: (1) event data based on diagnostic systems and failures, and (2) sensor data which relies on current component conditions. However, not all data is analysed or used. In-house knowledge is not sufficient to be able to transfer all data. Currently, too much data is generated such that it becomes difficult to distinguish and prioritize data. The quality of data highly depends on the data source, this should be accurately representing real and actual data. Finally, data is partially owned by NS, depending on the rolling stock type and contracts drafted with stakeholders.

2.6.4. Potential AR applications

Figure 2.4 presents potential AR application solutions specifically mentioned by the interviewee. The most frequently mentioned examples were: (1) fault detecting, (2) providing work descriptions, (3) inspecting components, (4) remote control, and (5) assistance for specialized work. Different AR application fields can be distinguished. Maintenance application fields offer the best potential for AR technologies. In total, 72% of the interviewees consider maintenance as a good application field.

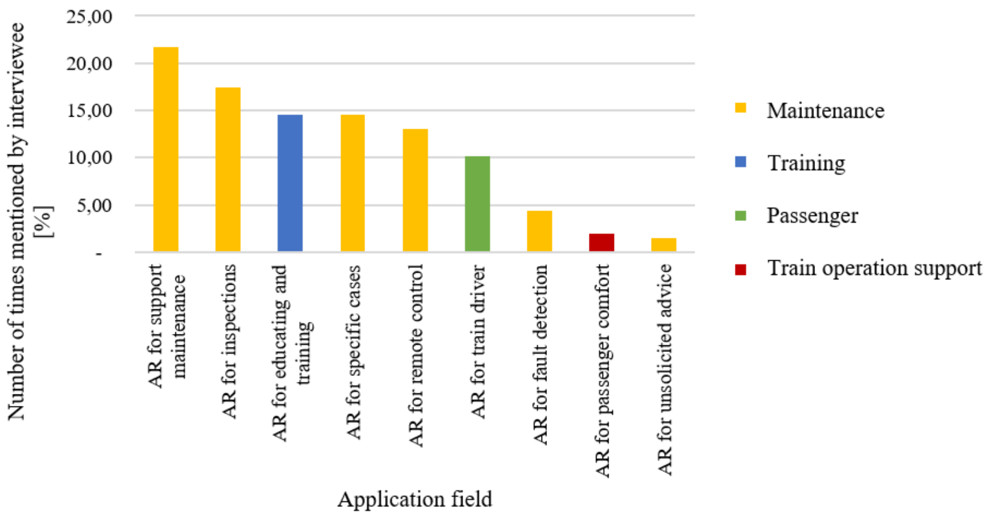

Figure 2.4. Potential AR applications based on qualitative field study.

2.6.5. Transition maintenance procedure

Maintenance operations are currently more based on performing corrective and preventive tasks rather than predictive tasks. New IT/OT systems require a different maintenance setup and thus a new and improved maintenance concept. The life cycle of IT systems is significantly shorter compared to hardware systems. Digitized rolling stock can self-diagnose failures by sensing and monitoring current rolling stock component conditions. In the future, NS aims to perform primarily predictive maintenance by gathering and analysing data on the way to Prognostics and Health Management. Failure complexity and transition of maintenance procedures are important to consider as well. When new technologies are introduced, local ambassadors are often used. Local ambassadors test and promote new technologies. Based on the field study, it is estimated that 75% of the technicians will accept the new technology if the tool is user-friendly and supports the work. The AR technologies should be developed in such a way that the use of them does not require intense additional learning trajectories.

2.7 Discussion

Due to different systems and technologies, machine interfaces are highly complex. From the qualitative analysis, the following benefits of digitization can be drawn: (1) safe and reliable operations, (2) less downtime, (3) less maintenance cost, (4) and on-time travelling. The Ishikawa diagram showed that the following root causes can be formulated: (1) increased complexity of IT/OT converged systems, (2) entanglement of failure types, (3) involvement of different stakeholders, and (4) transition towards digitized maintenance operations.

2.7.1. *Root cause analysis*

IT/OT will become increasingly important for the railway industry in the next decade. Operating systems such as cybersecurity and operating physical components are relevant for IT/OT converged rolling stock. Not all converged IT/OT systems have the same, safety requirements, reporting structure, and environment. This means that configuration management must always be up to date.

Failure types highly depend on component lifecycle, knowledge of systems, and complexity of procedures. Based on the Ishikawa diagram and the qualitative field study, the most common failures are (1) connection failure, (2) IT/OT complexity, (3) mechanical failure, (4) software bugs, and (5) insufficient configuration management. Most failures are caused by complicated IT/OT systems which are often badly understood by the asset manager. This complicatedness is caused by having different and more IT systems on the rolling stock and the interdependency of those systems. Due to the digitization of rolling stock, new rolling stock possesses more and different functionalities. Current maintenance operations need to be transferred into digital-oriented and data-based approaches. Structured, complete, and clear data is required for AR tools. Proper data sources are not always available, resulting in inaccurate data. Also, data exchange systems are not up-to-date on all occasions. Rolling stock data, such as sensor and event data, is gathered and stored in a centralized data repository. The transition to a digitalized maintenance concept creates opportunities to use AR for failures related to converged IT/OT rolling stock.

Different stakeholders are involved such as system integrators, (sub)contractors, and technicians or engineers. Clear collaboration is required to transfer knowledge between stakeholders. Currently, technicians and engineers have limited IT knowledge which is required for configuration management and maintenance of those new technologies.

Specific AR maintenance application fields are (1) fault detection, (2) inspections, (3) unsolicited advice, (4) remote control, (5) special cases, and (6) support of maintenance tasks. Applying AR in maintenance operations ensures early identification and a better understanding of failures, analysing and visualizing component degradation, remote control and assistance, work instructions, assistance for specialized work, and alerts technicians when performing high-risk tasks.

Acceptance of new technology is key when it comes to introducing AR. Concepts need to be introduced properly, preferably by using local ambassadors. The added value of the new technology must be clear and user-friendly.

2.7.2. Future directions

In the next few years, the transition into digitized maintenance operations will be extremely important for the railway industry as data and real-time monitoring are paving the way towards predictive maintenance procedures. To achieve this, data needs to be exploited for both analysis and making causal connections. Data regarding IT/OT failures needs to be more structured, organized, and prioritized before being able to get a better insight into systems. Information management must be clear and ensure secure operations. Both IT and OT departments are required to collaborate for broader knowledge sharing. AR opens the way towards structuring and recognizing failures of digitized rolling stock. It is therefore strongly believed that AR is a proper tool to be deployed for maintenance operations in the railway industry.

2.8 Conclusion

The research presented in this chapter suggests that identification, prioritizing, and solving failures of IT/OT converged rolling stock can be performed by using a tool such as AR. Relevant research challenges and future directions in applying AR to complex environments are proposed. Regarding the deployability of technology, it has been shown that the tool can be used in different applications of maintenance operations. In this chapter, a novel direction for providing future directions of AR in maintenance operations for IT/OT converged systems is proposed which allow non-experts to make top-level decisions. AR can be used as a tool to support maintenance operations by identifying, structuring, and providing solutions to IT/OT failures of digitized rolling stock.

Although AR has been proven to have good potential in maintenance, repair, service, and inspection, many of these applications are still at the prototype stage and have not found significant adoption in the industry. Looking at the industrial sectors where AR has been used, it is difficult to identify a sector that is especially benefitting from AR technologies [47]. Many technical studies were carried out only in laboratory settings, without implementing the AR system in a real context [38]. Existing real-case scenarios lack AR solutions that target specific areas. Prototyping of AR technology in combination with maintenance operations should be evaluated. Different case studies are required to analyse the effect AR has as a tool for identifying, structuring, and solving IT/OT failures. Experts from the industry can verify proposed solutions before the direct adoption of results. Other future works will include the implementation in the process of a tool for assessing the ergonomics and economic aspects of the AR application.

Chapter 3 – How to make augmented reality a tool for railway maintenance operations: Operator 4.0 perspective

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Changes: This chapter is translated from United States to British English and the terminology of train(s) is replaced by rolling stock

3.1 Theme II: Operator 4.0: Perspective and decision-making

In the last few decades, several initiatives and approaches have been set up to support maintenance procedures for the railway industry in adopting the principles of Industry 4.0. Contextualized maintenance technologies such as AR overlay can integrate virtual information on physical objects to improve decision-making and action-taking processes. Operators work in a dynamic working environment requiring both high adaptive capabilities and expert knowledge. There is a need to support the operators with tailored-based information that is customized and contextualized to their expertise and experience. It calls for AR tools and approaches that combine complex methodologies with high usability requirements. The development of these AR tools could benefit from a structured approach. Therefore, the objective of this chapter is to propose an adaptive architectural framework aimed at shaping and structuring the process that provides operators with tailored support when using an AR tool. Case study research is applied within a revelatory railway industry setting. It was found that the framework ensures that self-explanatory AR systems can capture the knowledge of the operator, support the operator during maintenance activities, conduct failure analysis, provide problem-solving strategies, and improve learning capabilities. This chapter contributes to the necessity of having a human-centred approach for the successful adaption of AR technology tools for the railway industry (Figure 3.1).

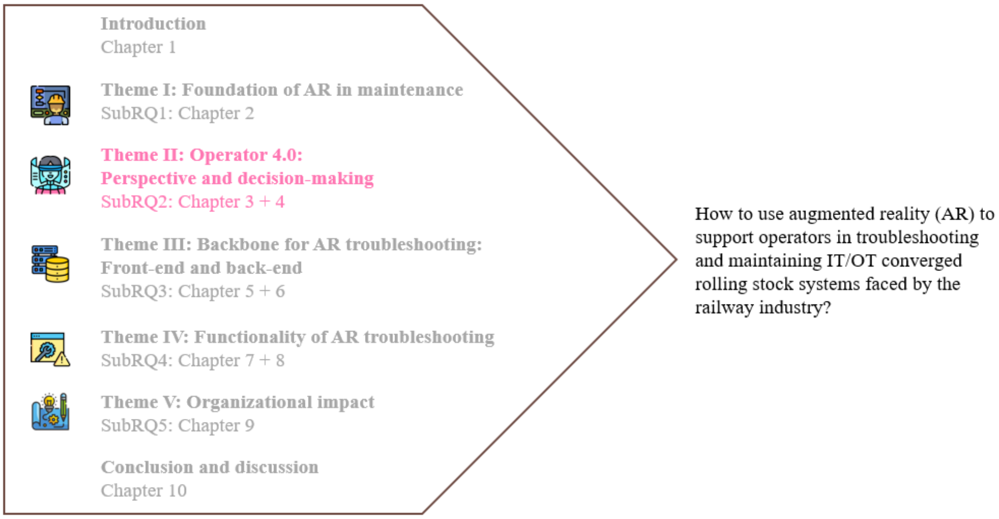

Figure 3.1. Theme II: Operator 4.0: Perspective and decision-making.

3.2 Introduction

Maintenance, repair, and overhaul (MRO) are critical areas in railway asset management and are crucial for industry growth and seamless railway operations. Asset management, also referred to as engineering management, ensures proper management of assets throughout their entire lifecycle [48]. Having a holistic approach to asset management establishes an important link between operational performance and management practices [49]. This holistic approach is key when managing risks and opportunities to achieve the desired balance between cost, risk, and performance. Attention should be paid to aligning asset management strategies with the overall organizational strategy across different levels of decision-making to contribute to practice-oriented and technical aspects [50]. In light of the above, maintenance plays an important role in physical asset management and contributes to operational performance.

3.2.1. AR Technology

Globally, the railway industry is focusing on attaining efficiency in MRO by accelerating maintenance and repair activities through industry-specialized AR technology solutions [51]. The global AR industry for the MRO market was valued at \$403.3 million in 2018 and is expected to reach \$3319 million by 2024 [51]. AR-based innovations have received a lot of traction in the last few years. In just over a decade, AR has matured and proven to be an innovative and effective solution to help solve several critical problems to assist and improve maintenance processes before they are implemented [52]. This technology is based on human-computer interaction and overlays digital virtual information in the real-world environment. The information display and image overlay are context-sensitive and user-dependant, meaning that they depend on the perceived objects in combination with the user's expectations. This technology enables railway companies to examine, monitor, and analyse rolling stock components with great effectiveness and efficiency. The evolution of technologies such as cloud computing, cognitive computing, and ML is paving the way for the growth of AR in MRO [53].

3.2.2. AR application fields

Besides maintenance, other AR application fields can be specified like medical, military, robotics, education, and geospatial [54]. AR assists in standardizing and making workflows more user-friendly and efficient by contextualizing and personalizing information. Although AR has great potential, the hardware is not yet user-friendly [55]. Recent work introduced the use of AR as a tool for processing and visualization of imaging data which can be subtracted from medical devices such as MRI scanners, simulation of surgical tools, and other assistive data [56]. This integration of the physician with the data and sensors ensures the visualization of patient data in 3D and collects and analyses newly generated data. However, subjective assessment of ergonomics and functionalities from end-users was used for minor improvements on the interfaces. Besides this, the AR tool must be seamlessly integrated into the daily workflow of the clinical site. To accomplish this, further developments in the AR hardware are required.

In the context of geospatial experiments, research has been conducted on defining requirements for hologram positioning and display [55]. The presented work contributes to optimized experimental user testing in a real 3D spatial layout. It was concluded that as long as reliable and accurate tracking cannot be provided by the AR tool, the use of the device will be limited to spatially confined environments.

The construction industry faces the problem of determining the location of underground utilities before excavation work can be carried out [57]. AR can be useful for field workers for work planning and during excavations. Research showed that field workers want to implement a finished version of the AR prototype tool for utility excavations [57]. Important functionalities for the operator were distance measuring, an estimate of leakage locations, and planning and coordination with other professionals.

Other new research describes innovative methods to integrate AR technologies with other technologies such as positioning sensors, tools for managing and visualizing geospatial data (GIS), and systems using high-precision real-time kinematics (GNSS) [58]. The main criticism from the end-user was directed to the casing of the device. Additionally, work needs to be done in delivering a physical and cognitive ergonomic device which will facilitate the job of the operators and make their life easier during the field activities. Moreover, the maintenance industry is facing significant challenges nowadays in which costs, safety, availability, and reliability are demanding objectives [59]. In recent years, the evolution of digital technologies has given analogue devices a digital footprint. This enables greater connectivity and provides possibilities to achieve higher levels of productivity and thus contributes to the objectives of the maintenance industry [60]. The integration of new digital technologies becomes possible and introduces the term “Industry 4.0”. This requires a quick and efficient maintenance service to guarantee that companies implement an efficient production system [61]. An important characteristic of Industry 4.0 is the exploitation of data to evolve from scheduled, control-based processes and systems to smart processes and systems.

Opportunities arise to predict the behaviour of operators, machines, and systems allowing faster decision-making and less downtime [8]. Predicting maintenance enables getting a holistic view of data sources, collection, and analysis to preserve asset reliability and management [60]. Integrating the Industry 4.0 paradigm in maintenance operations will have far-reaching consequences for the interactions between humans and technology [62]. The role of the human shifts from mainly being a spectator and machine operator towards a strategic decision-maker and a flexible problem-solver [63]. Due to the increasing complexity of production, humans need to be supported by assistance systems [64]. These systems need to aggregate and visualize information in an understandable way such that humans can make well-thought-out decisions and solve urgent problems on short notice. The focus of this research has turned to operators and the support given to them when performing a maintenance task. This study focuses on critical activities that take place on the shop floor of the maintenance facility.

AR can be useful for many situations in maintenance where users require real-time additional information tailored to the activity. Furthermore, if properly used and developed, AR visualization capabilities can transform maintenance processes [65]. Despite the visualization capabilities AR offers, the use of contextualized and customized information supply can be further explored. Not only will this contribute to the development of novel AR adaptive tool devices, but it will also convince users that they will forego traditional methods and opt for AR-assisted solutions.

New interactions between humans and AR support tools and the digital and physical world will directly influence the operator and the nature of work. Operator 4.0 is an experienced operator who can work cooperatively using human-machine interaction technologies to address complex problems [66]. However, not all operators have the same level of expertise, skills, preferences, expectations, and learning capabilities. An appropriate level of detailed instructions should be provided to the operator, tailored to their needs and expectations. Through AR, virtual information that is needed to support maintenance operators can directly be overlaid onto the real workspace. Novice operators can easily get real-life and real-time instructions, whereas off-site experts can collaborate remotely with them. AR guidance could significantly increase the efficiency and effectiveness of the maintenance operation, increase people and process safety, and minimize unplanned downtime [67]. Moreover, it is needed to support the operator to understand, map, and develop his/her competencies by developing an adaptive tool to provide tailored information to enhance the operator's task performance. To reach this goal, it is needed to provide a structured process that allows a systematic approach to using the adaptive tool.

3.2.3. Scope

The purpose of this work is to propose an adaptive architectural framework for a structured procedure that enables a systematic approach to provide support to operators using an AR tool. This tool should support everyday practices and facilitate adaptive capabilities. This adaptive architectural framework can be used for everyday maintenance tasks by capturing the know-how and helpful tips of more experienced operators. Based on experience, expertise, external factors, and the current condition of systems, the operator will be able to get access to tailored information at the right time. Figure 3.2 shows the main focus points that will contribute to the need for a dynamic tool. This research mainly focuses on the following aspects: (1) Operator 4.0, (2) AR capabilities, and (3) maintenance operations.

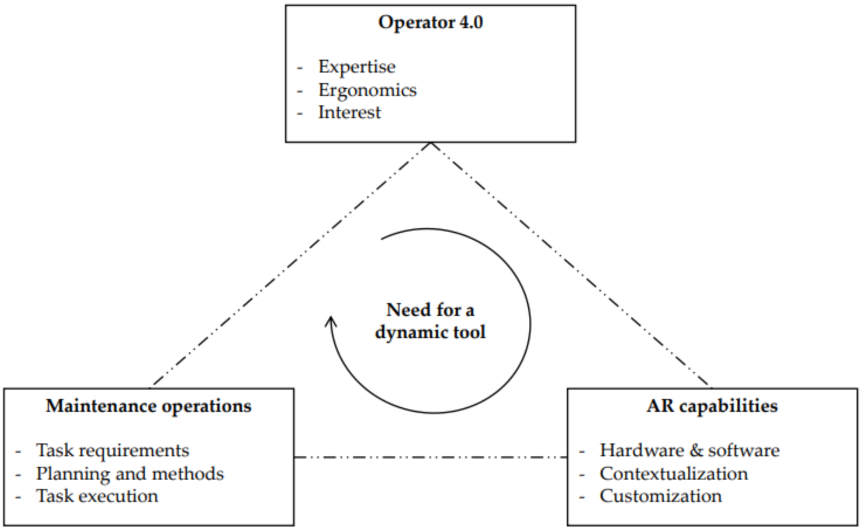

Figure 3.2. Focus points of the adaptive architectural framework.

3.3 Theoretical background

The research objectives identified in the previous section indicate the need to review the existing literature. The description of the focus points is presented in Figure 3.2. Each step is explained in detail in the following subsections.

3.3.1. AR in maintenance operations

To ensure continuous system performance in their present operating context, efficient maintenance planning and task execution are required. A maintenance plan contains consolidated listings with descriptions of the condition monitoring, time or usage-based interventions and failure-finding tasks, the re-design decisions, and the run-to-failure decisions [68]. To systemize the process for determining the appropriate maintenance task requirements, the application of the AR tool will be explored using the adapted Reliability Centred Maintenance (RCM) process steps [68].

- *Step 1:* Select equipment. In the first step, the operator must decide what to analyse. Each system component has a unique combination of failure modes and failure rates [68]. When a failure occurs in a system, the operator should prioritize and analyse the impact each failure has on the process. High-impact failures have high priority.
- *Step 2:* Determine the functions. The function of a system determines the action that it will perform. AR spatial mapping and tracking systems can be used for finding all major and less obvious failures in a system [19]. An operator can overlook less obvious failures, whereas the AR tool can capture and report all failures.
- *Step 3:* Describe failures. Overlapping virtual information to physical components, according to their real-world position, ensures the identification

of the failure. The operator can see that the virtual image and the real object are not in the same place.

- *Step 4:* Describe failure modes. A failure mode indicates how the system fails to perform its function [68]. Maintenance interventions such as checking, changing, and condition monitoring can be performed using AR.
- *Step 5:* Select maintenance action. Based on predefined actions and instructions, the operator can address the failure using tailored AR guidance and contextualization.
- *Step 6:* Document results. Technical manuals often recommend a maintenance method for certain equipment and systems. However, manuals or work descriptions are not often tailored to a particular operating environment and actual environmental conditions. The technology can capture the time needed for addressing the failure and what sequence of tasks has been performed. Hereafter, the technology provides a periodic intervention to eliminate failure to occur.
- *AR solution:* Select a flexible tool. This tool should assist the operator by systemizing the maintenance procedure. Besides this, the tool should contextualize and customize the information supply to the needs and skills of the operator. This support tool should easily be embedded in everyday maintenance operations.

Figure 3.3 presents the use of AR within a maintenance problem-solving process. The focus of the AR support tool is on sensing all failure causes, providing visual guidance in problem-solving, and alerting the operator if a task is performed incorrectly. The tool also monitors and reports the time and sequence of steps required to perform the maintenance task. An accurate indication of the time needed to perform a task can be captured. Maintenance planning and schedules can be adapted to this information.

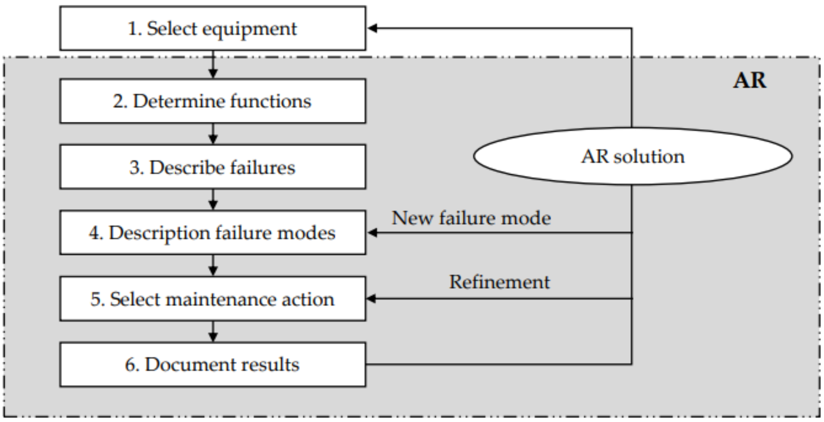

Figure 3.3. Added value AR offers maintenance procedures adapted from Campbell [68].

3.3.2. Operator 4.0: Augmented operator

Maintenance operations, in which the human workforce has a crucial role, need instruments able to manage complex systems. Nowadays most of the lower-skilled human jobs were eliminated and replaced by technology. This results in the remaining jobs becoming more complex, and comprehensive, and increasing the importance of interdisciplinary cooperation [69]. Consequently, numerous complex, high-precision processes are and will be managed manually. However, many of them could collaboratively be executed by humans and interactive technology cooperation.

Several factors are important regarding work satisfaction and dissatisfaction, including the work environment, work organization, and whether the work is interesting [64]. The operator's cognitive ergonomics, interests, and expertise should be included carefully since interaction with the real and digital systems is established. During this process, the operator's physical and mental workloads are affected by both system and process features as well as by external factors. Operators produce a subjective experience depending on the surrounding environment, individual skills and characteristics, and task features [69].

In an augmented environment, the Operator 4.0 typology considered is the augmented operator [70]. More specifically, the augmented operator owns a superior knowledge of the working environment which is not only derived from the daily interactions related to the maintenance task or procedures but incorporates a variety of value-added contents that are suited to augment his/her skills and abilities to perceive and act within the working environment [71]. Operator 4.0 is expected to benefit from the information and guidance generated within the virtual context. Applicable resources that usually may not be available should be made available directly using interactive technology. Besides this, a remote consultation tool to get easy and fast information and advice, and a tool for safety and security enhancement has to become available. The AR technology ensures lowering the cognitive load of the operator, as the operator does not have to manually search for filters according to the current context, or interpret information on a screen, rather they can visualize it directly on the target object [72].

From a business perspective, maintenance KPIs can be analysed that allow managers to have a proper overview of workstations and production lines in real-time monitoring [72]. It becomes possible to identify, analyse, diagnose, and resolve errors to keep maintenance processes moving towards operational efficiency.

3.3.3. AR capabilities

Nowadays, the operator knows the current state of a component by consulting a paper or digital work description containing the right configuration and information. Instead of forcing the worker to waste time consulting paperwork and interpreting the information provided in the work instructions, the proposed technology projects directly on the component giving accurate maintenance instructions and relevant information.

AR is considered key for improving the transfer of information from the digital to the physical world of the smart operator [73]. Moreover, AR has incorporated capabilities to new human-machine interfaces to maintain IT applications and assets. It displays real-time feedback about the smart maintenance processes and assets to the smart operator to improve decision-making. This technology supports the smart operator in real-time during manual maintenance procedures by becoming a digital assistance system [72]. Hereby, the operator reduces the time used for reading printed work instructions and documents, looking at computer screens or tablets, and following strict procedures. Operators no longer need to run the risk of using old or outdated paper documents and instructions. Digital information systems provide operators with the latest updated information. Other advantages the tool provides for the operator are its ability to offer intuitive information and combine operator intelligence and flexibility with error-proofing systems to increase the efficiency of manual steps [74]. AR offers a powerful tool for supplying the operator with contextualized and customized information [75]. Altogether, AR can improve the quality, reliability, and maintenance time, and reduce the failure rate.

Operator 4.0 will have access to the data coming from the rolling stock components and sensors in the maintenance facility. Besides this information source, knowledge can be gathered from other operators in the maintenance facility or even outside the facility from professional (social) networks. All information needs to be delivered to the operator and adapted, contextualized, and transformed to make it understandable such that decisions can be made resolutely and thoroughly.

3.3.4. The need for a dynamic tool

As the complexity of the maintenance operations grows, proper support tools and approaches are required for the operator [64]. Research suggests that Operator 4.0 is required to be highly flexible and should demonstrate adaptive capabilities in a very dynamic working environment [76]. Therefore, a need exists for an AR tool to support the operator in his/her daily work. Depending on the task environment, condition of the asset, failure description, level of expertise, and operator experience, the AR tool must provide tailored contextualized and understandable information into the operator's space in coexistence with real-world objects. To implement AR in the railway industry, the system has to be easy to maintain and modify. New content management tools are required as well as reconfigurability systems. The visualized information must be tailored to the operation and environment. Additionally, the way information is brought to the operator has to be studied. Future AR systems must be adaptive and able to systematically capture the operator's intentions in performing a maintenance task. Besides this, it should collect the data of any maintenance procedure. The information collected could be used to improve the training process of the tool or the maintenance procedure itself. Before the tool can function as a support system for the operator, a structured approach should be proposed to systemize the adaption process. As can be seen in Figure 3.2, the realization of the tool requires a structured framework.

3.4 Methods

The developed adaptive architectural framework aims at accelerating the adaption of information supply assistance that AR provides to the augmented operator. The framework will help to understand what information should be captured, why this should be captured, how it must be captured, and how the data is being reused for future AR experiences. In the following, the basics of the underlying decision support system, as well as boundary conditions and requirements are presented as they form the basis of this work.

3.4.1. Decision support system

A human-centred approach to capturing the knowledge of an operator is the decision support system. The AR tool is used to capture expert knowledge on maintenance task performance. The aim is to mimic how experienced operators make decisions based on using their experiences to form plausible approaches for new situations. Incremental learning for modelling complicated decision support systems is required to quickly retrieve information by representing and organizing experts' knowledge [77]. Gathering expert knowledge is vital for the development of (1) specific domain knowledge, needed to generate example solutions, and (2) general domain knowledge, needed to develop the reasoning structure. Applying an adaptive tool to a decision support system could assist a novel operator in a similar way to how an expert would use their experience to solve a problem.

The distribution model of cognition has been adapted for this framework and focuses on developing an ensemble of distributed individuals and artefacts [78]. This model considers two indispensable parts: internal and external representations. Internal representations are the knowledge structures in the operator's head that can be retrieved from memory. External representations are the knowledge structures coming from the environment. The environmental elements help to make sense of the dynamic working situation by providing information on physical symbols, objects, dimensions, constraints, and relations embedded in physical configurations [78]. Besides this, the environment provides information on what task is expected to be executed and who will participate in the procedure. The task that needs to be performed, together with external and internal representations, contributes to the mental representation of a task solution.

Opportunities arise for human and intelligent systems to collaborate, learn from each other, and work together to achieve common objectives. Effective collaboration can be established if the interactive technology is logical, explicable, and able to understand human cognitive processes [79]. A cognitive and interactive tool can learn and improve with an operator acting as a mentor for the system, based on his/her experience and knowledge, whereas the system provides feedback to the human in return [80]. For the operator, the process of providing feedback and interactions ensures both increased efficiency and developed confidence in the system [78].

3.4.2. Boundary conditions

Technical and technological issues related to the development and implementation of AR are debatable elements. Most studies that review technological solutions for visualization either use mobile devices with camera-overlay AR or HMDs with see-through AR [38]. Mobile devices need to be held in the hand when used and therefore potentially hinder maintenance tasks. HMD solutions leave the hands free, allowing for more natural and intuitive hand-based interaction with virtual objects. However, sometimes a limited view can be experienced by the operator using HMDs.

An operator's knowledge level must be established to verify the level of expertise an operator has. However, in real-life situations, it can be difficult to obtain an exact and reliable assessment of human competence. To estimate an operator's competence, different data collection methods could be explored, such as interviews, testing at the workplace, using empirical methods, and maintenance task simulations [76]. The collection of input data for competence analysis can be achieved by measuring the execution time of the maintenance task in the facility and evaluating the experiences of the technicians. For knowledge capturing, experienced operators must be recruited. To increase the effectiveness of the knowledge-capturing method, a large number of operators should be involved which is important for providing decision support.

3.4.3. Architectural requirements

The proposed architecture, apart from bringing together information from different digital databases, combines five major features by exploiting AR: (1) capturing the knowledge of the operator, (2) providing maintenance support, (3) performing failure analysis, (4) providing problem-solving strategy, and (5) providing learning capabilities. The adaptive architectural framework has been designed simultaneously while performing case studies. The studies are proving the value of the framework. The framework is based on the methodological decision support system and its main requirements include:

- Provide the augmented operator with real-time feedback and AR content on tasks/procedures execution. Operators are guided by the supplying of visual and audible instructions to give tangible feedback.
- Based on expertise, experience, external factors, and current conditions of the component, it is required to ensure the operator has a personal tailored digital knowledgeable assistant to interact with. Depending on the operator's ability, noncritical information can be supplied using subtle instructions in different visible frequencies.
- By capturing the knowledge of the operator and procedural steps, the system can learn from previous maintenance procedures. The time and sequence of steps used to perform a maintenance task can be captured and reported. This can indicate how much time is needed in the future to perform the task.

Moreover, failure rates can be compared to this information, providing insight into the most sustainable procedure. Maintenance planning and schedules can be adapted to these accurate findings. Therefore, the efficiency of operation support will be increased.

Based on the architectural requirements, a functional analysis is presented to structure and identify potential solutions that exist for the adaptive tool. In Figure 3.4, the most viable solutions are proposed. The analysis explores potential solutions for a given function, the solutions are variable.

Function \ Solution	Manual system	Sensor system	Interactive system	Augmented system	…
Capturing knowledge operator	Manual assessment by supervisor or operator him/herself	Experiments, interviews, simulation models	Tracking time and sequence of steps	Gesture tracking systems	…
Providing maintenance support	Static step-by-step guideline	User-tailored task description	Remote support	Augmented task illustration	…
Performing failure analysis	Static catalogue of typical failures	Reading sensor diagnostics	Displaying diagnostics automatically	Systemized experience and expertise tracking	…
Providing a problem-solving strategy	Manual task performance	Adaptive task performance	Contextualized task performance	Visualized task performance	…
Providing learning capabilities	Manual assessment of task performance	Stand-alone digital feedback system	A collaborative learning feedback system	Dynamic multiple feedback	…
Generating interactions	Human interactions	Programming, modelling, knowledge management	Adaptable system to transfer knowledge	Reconfigurability of systems	…
Assessing cognitive workload	Subjective questionnaires	Physiological parameters monitoring	Stress analysis	Motion capture system	…
Continuous assessment procedure	Verification by operator	Real-time condition monitoring	e-maintenance	Intelligent prognostics tools	…
Capturing results	Documentation on paper	Process monitoring	Object detection and instance segmentation	Capture contextualized and customized data	…
…	…	…	…	…	…

Figure 3.4. Functional analysis of adaptive capabilities and potential solutions.

Based on the functional requirements from Figure 3.4, the architecture in Figure 3.5 has been designed and implemented in the maintenance process analysis of Figure 3.3.

- *Step 1:* Select equipment. The goal to be achieved is formulated. The operator will be guided by visual and audible instructions which also give tangible feedback.
- *Step 2:* Determine functions. The task that needs to be selected to reach the goal is stated. Besides this, the adaptive AR tool provides all failure causes and digital information on all potential solutions. It will let the operator be aware of the context to gather relevant information and/or services, relevancy depends on the operator’s tasks [81]. Using context awareness systems, such as AR, accurate access to maintenance information is provided such that the operator’s performance efficiency can be increased.

- *Step 3:* Describe failures. Initiation and evaluation of the operator's expertise is currently based on the operator's or manager's perspective. The level of expertise varies from having no clue what is going on to being an expert and being able to train others. In this framework, initiating the level of expertise is performed manually but can become an automized process in the future. Operators can be equipped with sensors to activate psychomotor and cognitive responses that are beyond what operators can verbalize. Capturing gestures of experts can improve interactions with AR and ensure future knowledge capturing [78].
- *Step 4:* Describe failure modes. Dynamic behaviour capturing is required to perform a successful fault diagnosis [78]. Based on time and process tracking, the operator should know what initiated the fault, what the current situation is, what is needed to solve the issue, and what time is required to solve the task. Varying business demands changes in work routines, resource availability, and environmental conditions. Depending on the complexity and nature of the maintenance task, the operator adapts his/her maintenance concept.
- *Step 5:* Select maintenance action. The tool presents the task that aims to restore the functionality of a system. The actions that can be performed to restore the functionality of the product can be technical, administrative, and managerial [75]. Continuous assessment takes place of the operator's performance, task condition, and other external conditions. Besides this, the tool will send warning messages of improper maintenance operation execution. When the task or business demand increases, mental demand increases resulting in negative effects on physiological variables [82]. The likelihood that the operator fails in performing his/her task becomes subsequently larger, it is therefore needed to have a control or monitoring system that alarms the operator when tasks are not performed adequately.
- *Step 6:* Documents results. Documentation can support the detection of schedule derivations or the search for sources of defects and the responsibility of the operator [83]. Adequate process monitoring methods help managers and operators to document the current status of the maintenance work as well as to understand origins and defects. Some maintenance tasks require inactive input, for instance, to leave comments on specific objects. AR allows storing these annotations directly in relationship to the real environment.
- *AR solution:* Select a flexible tool. Incorporating different types of data, interfaces, visualization systems and sensors makes the adaptive tool applicable to multiple solutions.

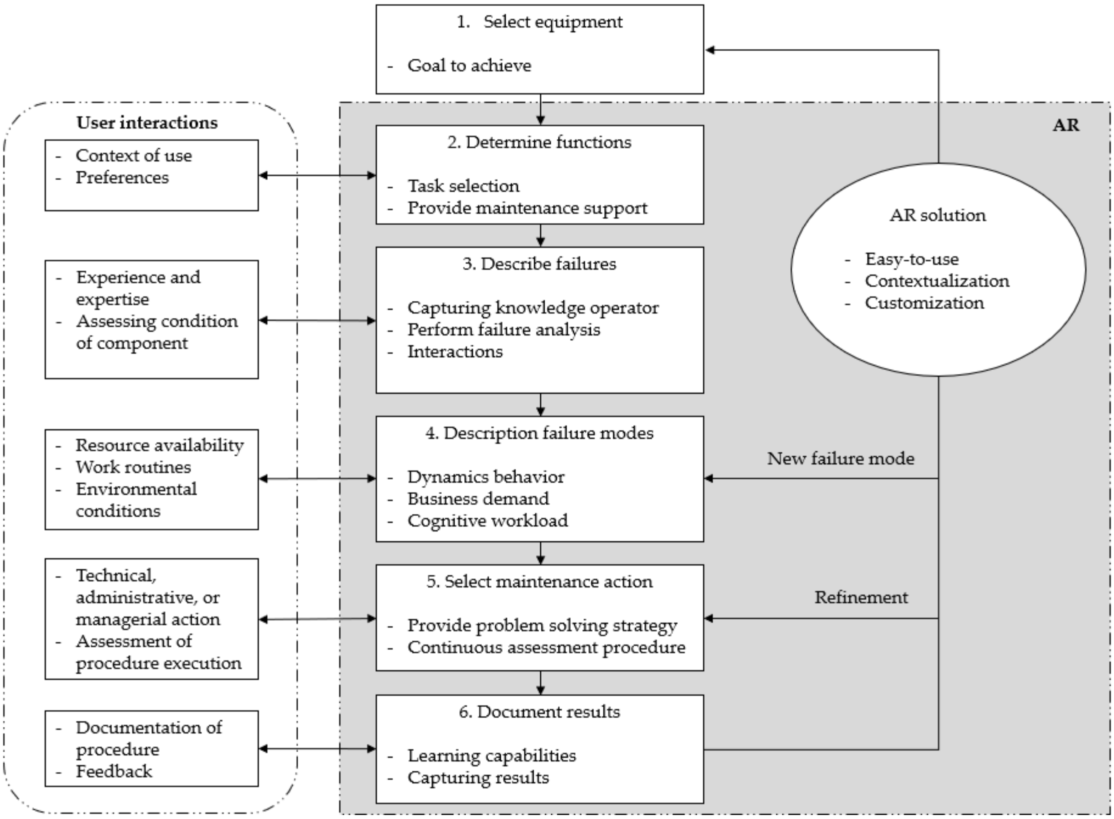

Figure 3.5. Schematic of the adaptive architectural framework.

3.5 Case study

The purpose of a case study is to explore and depict a setting in which the researcher exploits data from direct observations and systematic interviewing from public or private archives [84]. This case study aims to increase understanding of the need for having an adaptive architectural framework to support Operator 4.0. The case study helps to identify technology adaption patterns, define requirements needed to support the operator and provide future steps needed for application in maintenance operations.

3.5.1. Case study characteristics

In this research, one single case study is examined for validation of the framework creating the opportunity for in-depth observation. This framework allows for a two-way learning system. More specifically, not only does the case study present the effects of the framework, but the framework iterates after the case study is explored. An example of using one single case to examine reengineering service operations is performed by Narasimham and Jayaram [85]. Other research focused on motivating operators to make active decisions when transforming IT function profiles in healthcare organizations using one single case study [86]. More recent work examined the process of resource alteration underlying the digital manufacturing journey using a single case [87].

The NS is a Dutch state-owned company and the principal railway operator in the Netherlands. The Dutch rail network is Europe's busiest and will only become busier [88]. Among others, NS aims to achieve safe, sustainable, and reliable operations in which technological developments are key [89]. The company recognizes the added value AI, the IoT, and AR have to improve services and contribute to efficient operations. Additionally, they have noticed that the coronavirus is accelerating digitization and technological developments. In short, NS offers great opportunities to exploit a case study for framework verification.

Several information sources have been used throughout the research such as interviews, managerial presentations, student thesis on maintenance operations, and public, and internal documents. Multiple interviews with managers and operators were held online. The participants were selected based on their knowledge of innovative technologies, data collection and management, and maintenance operations. In total, 28 participants were interviewed of which the majority are part of the NS technical department. This sample size represents 35% of the total sample size and is sufficient for this specific knowledge field [43]. The length of the interviews varied from 30 minutes to 1 hour. The interviews provided deep insight into actual focuses, potentials, and challenges that the case should include. Based on the information sources, a case description was prepared and verified by the company. To increase the framework's validity, the completed version was discussed, completed, and improved with the company.

3.5.2. Investigation of the retractable step

Previous research was conducted within the Dutch railway industry for adopting VR technologies for training and skilling of employees, and to assist rolling stock drivers during specific operations [42]. In this research, the focus was put on increasing operational and training efficiencies. Notwithstanding the positive results AR can achieve, there are still a few questions that remain unanswered about the employability of this emerging solution. The verification of the usage of this adaptive architectural framework can be performed by exploring a case study for NS. For this case study, the Fast Light Innovative Regional Train (FLIRT) type is further examined. This rolling stock is a passenger electric multiple-unit trainset [90]. All interviewees agreed on the validity of the framework using this case.

The railway company investigated the failure mechanism of the FLIRT electric door system in which the retractable step caused the system to fail repeatedly [91]. This system serves to bridge the gap between the platform and the vehicle. Within 50 operation days, 187 services were requested for the door system. Since the deployment of the FLIRT rolling stock series on the Dutch railways in 2016, 1099 service requests were already made in 2017 [42]. The door system failure accounts for 17.4% compared to other failing components and is only surpassed by the communication system of the rolling stock which represents 27.5% of all failures [42]. The failing door system has, therefore, a high priority since it has a direct and great impact on rolling stock operations.

3.5.3. Failure description retractable step

The product description of the system is based on the technical documentation of the retractable step [92]. The entire system consists of the sliding step and the connection cable to the control unit. The extension unit consists of a frame in which the walking zone is stored. The walking zone is equipped with a step sensor and anti-slip coating. The drive takes place utilizing a DC motor. The motor is mounted on a compact drive-bearing unit. The driving force is transmitted from the motor shaft via a hollow shaft to a toothed belt wheel. The toothed belt wheel drives the central drive belt. A carrier on the toothed belt establishes the connection with the sliding step and converts the motor drive power into the extension movement of the extension unit. The sliding step is guided by profile rollers on the extension unit. The upper and lower rails are both made of stainless steel. The profile below the lower rail is made of aluminium. If a vertical load of 150 N or more is applied to the sliding step during extension or retraction, the movement is stopped immediately. A schematic overview of the rolling stock door retractable step system is provided in Figure 3.6.

Number	Component
1	Base frame
2	Slide-out unit
3	E-motor
4	Toothed belt
5	Cove plate (bottom)
6	Water outlet with pipe flange
7	Cover plate
8	Safety switch
9	Cable box
10	Connection cable (socket)

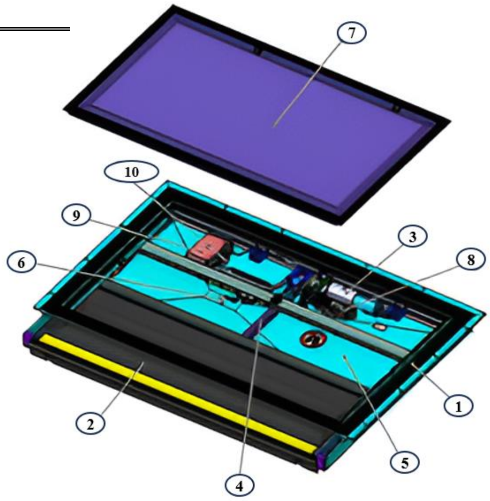

Figure 3.6. Component description FLIRT retractable step [91].

According to the research performed by NS, the FLIRT sliding step causes many problems [91]. The most critical problem is that the retractable step gets stuck due to clamping. In that research, clamping was caused by the fact that the left rail was raised about 2.4 mm. To find out why the bottom rail came up, a destructive test was performed. The part of the aluminium profile at the height of the elevation was cut out and the lower rail was removed. Details of the side profile with rollers are presented in Figure 3.7.

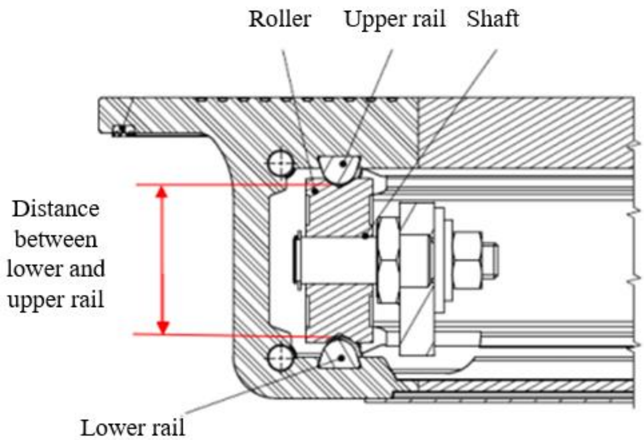

Figure 3.7. Details of side profile retractable step with rollers Fast Light Innovative Regional Train (FLIRT) [91].

The rise of the lower rail was caused by the formation of aluminium oxide between the stainless-steel rail and the aluminium profile. More specifically, it was caused by galvanic corrosion of the sliding step. The volume of aluminium oxide pushes the bottom rail up by 2.4 mm.

3.5.4. Application adaptive architectural framework

The application of repairing the retractable step in the designed adaptive architectural framework is presented in Figure 3.8. General specifications for the application of the framework to this case are:

- Decisions are made based on the operator's perspective on his/her level of expertise. Let the amount of AR information and frequency of information supply be adapted to the specific user, task demand, and business demand.
- Knowledge is captured from expert operators to use their experience to assist a novel operator in solving a problem. General and specific domain knowledge should be gathered to provide an incremental learning method. The time needed and the sequence of steps of the procedures involved can be derived from the task performance. Hereby, the operator and the company capture detailed knowledge of the procedure to become more efficient and adequate problem solvers.
- Safety and security measures should be taken into account more consciously. The framework ensures sending warning messages if procedures or tasks are not performed according to procedures or safety standards.

Some functional solutions from Figure 3.4 can be used for the case study by setting adaptive capability requirements. All solutions directly affect the user's interactions with the AR technology.

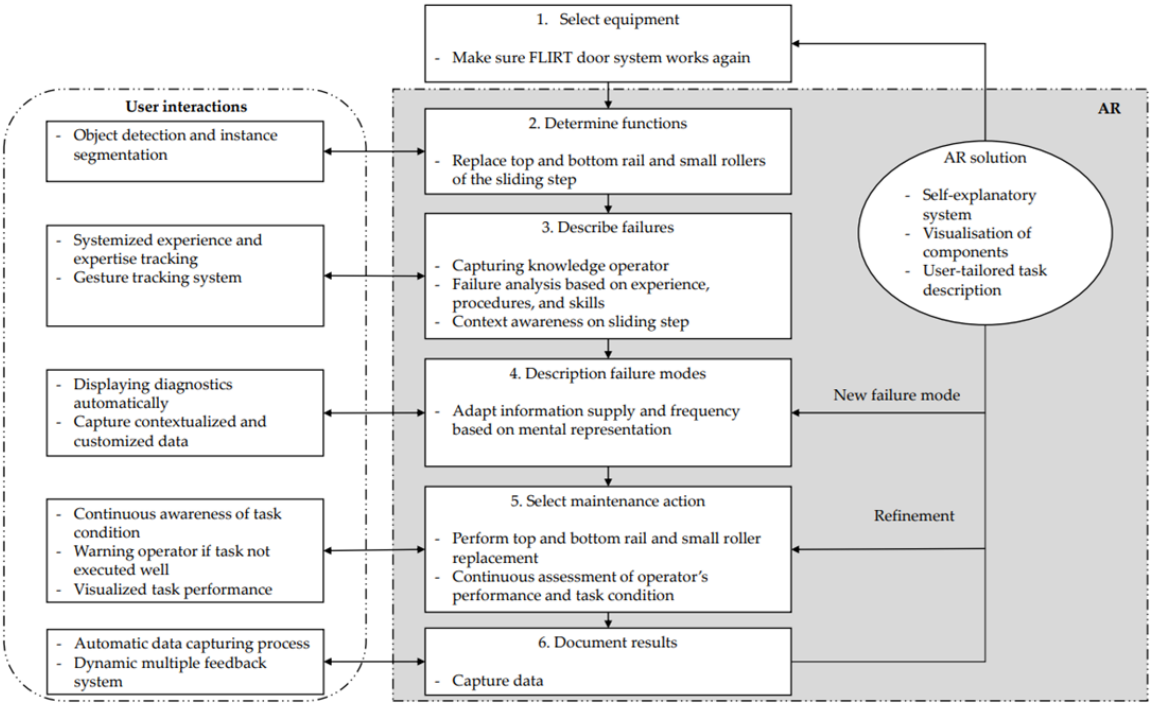

Figure 3.8. Applied case study for the designed adaptive architectural framework.

3.6 Discussion of the main results

The case study represents a unique endeavour about the importance of having a structured process to ensure support is provided to Operator 4.0 using AR. This adaptive architectural framework reveals what technology adaption patterns are identified. Besides this, requirements are provided to support Operator 4.0 in his day-to-day work. Finally, future trends are examined from the point of view of maintenance work.

3.6.1. Technology adoption patterns

Looking for technology adoption patterns, this research emphasizes the perceived ease of use of AR technologies, the perceived usefulness of the technology, and having self-explanatory systems. This contributes to better expectation management interaction and acceptance between the operator and the AR tool. Still, a lot of other technology adoption patterns can be found due to a lack of understanding of key challenges and success factors. Multiple hardware solutions can be proposed to enable adaptive instructions to operators. Research has been performed to assess AR tools to be implemented for practical everyday use [66]. This research investigates usability together with the achieved levels of productivity and quality. It was concluded that facilitating the operator with adapted displayed instructions is not only useful for novel operators but also for experienced users. Not only hardware is important when it comes to technology adoption, but ergonomics includes even more aspects of user acceptance. The study revealed that an inadequate design of the UI can lead to distraction or disorientation [93]. Apart from the adoption patterns mentioned before, the case revealed the importance of having an analysis of mental and physical demands. A recent study supports the main findings of the case study and identifies success in adopting AR in the industry by achieving: user acceptance, visibility of information, ergonomics, and usability of the UI [94].

3.6.2. Support requirements for Operator 4.0

This research suggests information provided to the operator should be based on real-time, contextualized, and customized data. The information supply (and the related UI) should be tailored to the expertise and experience of the operator, component condition, and other external factors such as organizational demand. The application of different visual computing technologies in industrial operator tasks was presented by Segura et al. [72]. They presented several cases to show how proper visual analytic systems can support the operator to better understand and easily detect wrong production situations. Their research emphasizes the need to adapt and balance procedures with the experience and expertise of the operators. As suggested by earlier research, Operator 4.0 can be empowered by adapting the machine-UI, machine behaviour, and planning [64]. Based on the operator, UIs of the AR tool could be adapted to allow only showing functions that the worker understands. This will facilitate in identifying the role of the operator, AR capabilities, and maintenance operations.

3.6.3. Future trends in maintenance operations

The case study depicts the ability to have an automatic data-capturing process while also having a dynamic multiple feedback system. Capturing maintenance operation data and knowledge of the operator contributes to incremental learning capabilities. Consequently, maintenance planning and schedules can be adapted to this. Hence, future operations support increases. Digitized systems recognize changes in operations and continuously update component performance [60]. Thus, ensuring optimum efficiency is always achieved. The maintenance operators can be supported with real-life instructions, diagnostic information, and remote assistance. However, the economic, environmental, and social challenges faced by the AR industry still require further investigation [67].

3.7 Conclusion

Although much progress in AR has been made in recent years, little attention has been paid to correct the integration of humans in the emerging context of AR in professional industrial (engineering) environments. A human-centred approach is necessary for the successful adaption of AR technology tools for the railway industries. Operator 4.0 will play an important role in facilitating the transition from traditional maintenance procedures to remote, digitized, and autonomous operations. Few in-depth studies assess and evaluate human factors and interaction in (industrial) AR systems [72]. Attention has been drawn to operators as a key element in addressing new and unpredictable behaviours in AR. Since operators experience an increased complexity of their daily tasks, an adaptive tool is desired to support the operators. Based on the operator's competence, expertise, component condition, and external factors, the tool will provide contextualized and customized information. Looking at the spread of previous research, it can be concluded that they all consider the need to (1) support Operator 4.0 interactive technology and (2) supply tailored-based information [18][25][53]. However, before tailored-based information can be supplied to support the operator, it is required to structure the process to enable systemizing this approach. Therefore, this research bridges the gap between the need to support operators using an AR tool and the approach to providing this.

The main research contribution is twofold: (1) proposing an adaptive architectural framework aimed at shaping and structuring the process that enables a systematic approach to provide a support tool to operators using an AR tool, and (2) a case study that implements the aforementioned framework. As a result, an adaptive architectural framework is suited to augment the operator's skills and abilities to perceive and act within the working environment. This digital assistant tool supports the operator with vocal and visual interaction capabilities. It is meant to provide quick, tailored, and efficient information on maintenance tasks.

The adaptive architectural framework can: (1) capture the knowledge of the operator, (2) support the operator in performing maintenance tasks, (3) conduct failure analysis to find all potential failure modes, (4) provide all problem-solving strategies, and (5) improve learning capabilities by documentation of procedural task performance. This framework can be adapted to be able to absorb and immerse the environment for preliminary training on new or complex procedures. To this end, the proposed adapted architectural framework is scalable and modular since the principle can be applied to different industries and infrastructures. Many companies are considering implementing AR solutions in their maintenance operations and are willing to perform several experiments using the technology [94]. From the proposed framework, this study suggests managers start exploiting opportunities for AR technology application fields. In a maintenance workshop, operators are directly linked to AR solutions. In this case, the relevance of structuring the process of providing customized and contextualized data to operators was considered. Using this framework, operators will find all potential failure modes of a component and define all problem-solving strategies needed to solve the issue. Therefore this framework increases the safety, efficiency, and availability of the operators. However, managers should be aware that the decision of this trajectory is costly. Besides the costs, managers should bear in mind that using AR strategies is only an intermediate element of the digitization of the company structure. Furthermore, the development of AR technologies continues and, therefore, organizations should be ready for frequent iteration and adjustments in application strategies.

Industry 4.0 is still an open research field where already much has been done but there is still more to do to accomplish its vision. This research proposed a forward-looking adaptive framework for Operator 4.0. From a technical point of view, additional work can be done to improve and optimize the technical performance of the framework in terms of capturing the operator's knowledge and transforming this expert knowledge into a database for the development of a decision support technology [77]. More specifically, future work is required in the specification of the expert level of the operators. Capturing knowledge is currently based on the perceived perception of the operator or manager. However, knowledge capturing should become autonomous [95]. In addition, verification and validation of the framework can be performed in a simulation and experimentation setting. Overall, the case study provides valuable insights and opportunities for ongoing improvements and development of the framework. A methodological limitation of this research is the use of one case study. Adding to this, the case was based on a limited number of interviews. The case provides useful information on an emerging topic like AR. But one case is still not enough to draw generalisable conclusions. Efforts and the involvement of other managers bear the opportunity to continue the current case. The external validity of the research could be enhanced by examining other companies in a similar situation. In terms of research perspectives, future work will be needed toward the development of prognostic capabilities. Integration of sophisticated algorithms for real-time monitoring and process control will support maintenance operations.

Moreover, the adaptive architectural framework contributes to the advancement of Industry 4.0 by addressing challenges related to IT/OT convergence and digitization in the railway industry. By integrating AR technology and leveraging operator knowledge, the framework supports the vision of Operator 4.0, where human operators are empowered by advanced technologies to enhance maintenance practices. The adaptive architectural framework promotes a human-centred approach by prioritizing the needs and capabilities of operators throughout the maintenance process. Furthermore, the systematic approach facilitated by the framework enhances operator performance by providing clear and structured guidance throughout maintenance procedures. Operators are guided through each step of the process, from equipment selection to documenting results, with visual and audible instructions that offer tangible feedback.

Chapter 4 – Supporting maintenance operator using augmented reality decision-making: visualize, guide, decide & track

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Changes: This chapter is translated from United States to British English and the terminology of train(s) is replaced by rolling stock

4.1 Theme II: Operator 4.0: Perspective and decision-making

In railway maintenance activities, sophisticated socio-technical interactions are required to achieve efficient and reliable operations. Maintenance technicians carry out their daily tasks based on expertise and knowledge gained from both training and personal experience. In rolling stock design, IT systems and OT systems converge, resulting in complex rolling stock failures, maintenance procedures, and activities. Troubleshooting rolling stock failures becomes extremely difficult and time-consuming as more data and information are available and filtering and selecting them becomes cumbersome. New technology developments and interactive interfaces and environments that speed up the process of understanding troubleshooting decision-making and facilitate design collaboration are required. AR is a technology that provides real-time, on-site, and structured information that offers great potential for visualizing, structuring and contextualizing data to facilitate well-considered choices for decision-making. Therefore, an AR decision-making tool is developed based on structuring, visualizing and contextualizing data in an AR solution space. The tool captures real-life system conditions, comprehends troubleshooting activities, facilitates problem-solving decisions, and tracks maintenance procedures. A case study validates the tool by implementing: (1) object recognition for visualization, (2) a what-if analysis for troubleshooting directions, and (3) capturing maintenance timing and procedures. This chapter contributes to streamlining and supporting well-informed decision-making in railway maintenance operations (Figure 4.1).

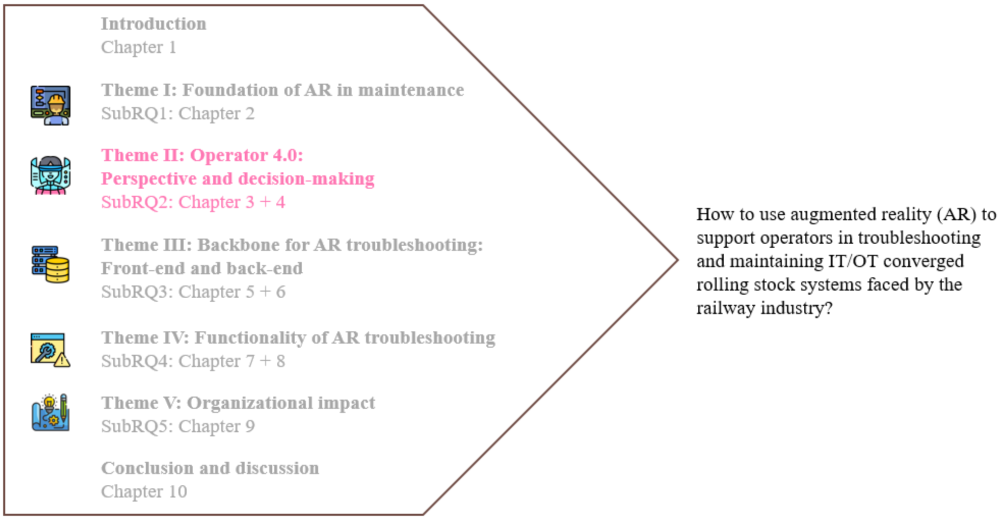

Figure 4.1. Theme II: Operator 4.0: Perspective and decision-making.

4.2 Introduction

To meet railway operation and safety requirements, life-cycle asset management is of utmost importance. These days, automatic prognosis or fault-finding support in maintenance is becoming popular [16]. Besides this, maintenance procedures are becoming data-driven and analysis of failures is even more complex due to the convergence of IT and OT systems [96]. Nowadays, systems of computational components and the adjacent world are combined resulting in three categories of failures: (1) cyber system failures, such as software errors, (2) physical system failures, such as mechanical errors, and (3) human failures, such as misusing systems or lack of expertise [97][98]. These failures increase the complexity of operations and affect workflow efficiency. Many of these failures are difficult to resolve by operators without decision support systems [99].

Connectivity, integration and process digitization emphasize increasing automation and autonomy of machines, with operators still playing an important and vital role in this technological evolution [100]. New technologies, such as AI, AR, and IoT, are now utilized in the decision-making process. Because it is difficult to understand complex failures, new technologies supporting the decision-making process are thriving to help operators understand rolling stock systems and their failure behaviour so that they can make maintenance decisions accordingly. However, the primary function of these technologies is not related to performing efficient, effective, and flexible decision-making. In addition, these technologies require a supporting architecture to apply them [100].

Given the increasing complexity of IT/OT rolling stock failures and limited time for maintenance, troubleshooting procedures are becoming more difficult, requiring technicians to make quick yet reliable decisions. AR is a technology utilized to support maintenance decision-making methods [99]. AR can be used to provide real-time, on-site, and step-by-step visual guidance in maintenance operations. Facilitating operators with AR technology in the decision-making procedures supports understanding complex IT/OT systems [101]. With the appropriate data filtering, selection, and translation, AR can visualize information and thereby make it understandable, resulting in the transmission of structured IT/OT information to the operator, facilitating decision-making and thereby supporting troubleshooting to increase productivity [101].

Altogether, AR brings real-life IT/OT system conditions into focus by visualizing information to better understand rolling stock failures and ultimately speed up the decision-making process for operators [102]. Therefore, the goal of this research is to create an AR tool that comprehends IT/OT system failures, facilitates troubleshooting and thereby assists operators in their problem-solving decision-making strategy. The AR tool records and tracks the maintenance activity performed and the maintenance execution time required. This information can be used for the development of future maintenance procedures.

4.3 State of the art

The growing interest in the fields of decision-making and AR and their combined potential offers the opportunity to address and understand the contributions provided by both. Combining these two fields paves the way to support operators anywhere at any time where information is collected from numerous sources and visualized using

AR, allowing operators to comprehend patterns from large amounts of information, increasing knowledge and awareness [101].

An example of AR decision-making is given in the embedded electronic field for training maintenance professionals [103]. The AR tool provides an interactive, learning tool that simplifies the procedure leading to a task to perform and thereby helping the operator. Other research investigates the extent to which AR can increase project performance in the construction industry [104]. The information enhancement and extraction process from building models are positively influenced by using AR. Also, participants from the project recognize the early discovery of design errors. However, in some construction companies, the IT department is sometimes not prepared in terms of data availability and infrastructure to adopt AR. Another AR decision support framework is STARE (SemanTic Augmented REeality) which integrates focal objects with compositions of semantically IoT data [105]. The focus of the study is to present an AR environment interface for high-level decision-making by utilizing decision rules and IoT data descriptors to superimpose suggestions over the focal object. The work includes using a rule store and a reasoning engine to construct the object and the corresponding associations. However, troubleshooting real-time scenarios and maintenance tracking are not included in the tool. For the successful use of AR in decision-making support, several factors play a key role, such as structuring and filtering relevant data for the operator, visualizing information, prioritizing task execution, and synthesizing priorities [99]. After examining the most recent publications in the fields of interest, it became apparent that there is still ground for researching the practical industrial application of AR decision-making support tools [106].

The novelty of this research focuses on the combination of ways to filter, select, and translate data into understandable information for the operator, capture real-life system conditions, support troubleshooting activities and facilitate decision-making through AR. For a maintenance AR decision-support tool, it is required to set up a data infrastructure that allows data filtering and structuring. Hereafter, the AR tool receives information about the relevant rolling stock system with its corresponding failure. The AR tool provides the capabilities to comprehend system conditions and visualize related information. Then, using what-if analysis, corresponding existing troubleshooting scenarios can be presented to guide the operator in resolving the failure. Since documenting maintenance activities is important to develop future procedures, the tool records and tracks the executed maintenance task and execution time. A schematic overview of the decision-making tool is presented in Figure 4.2 AR plays an important role in the highlighted boxes.

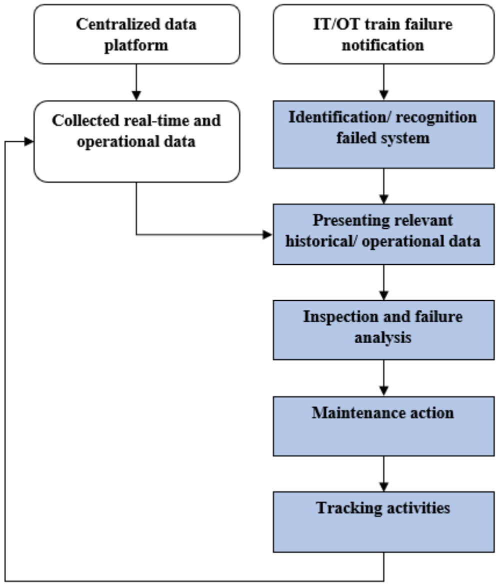

Figure 4.2. Schematic overview of AR decision-making tool.

4.4 Methodology

A qualitative field study is used to set up the preliminary requirements, expectations, and configuration of the AR decision-support tool. The design of the AR decision-making tool with its rules and algorithms presents the backbone of the model. This field study supports the importance of the research by understanding and visualizing decision-making choices in complex IT/OT troubleshooting procedures. To enhance the knowledge and understanding of the proposed AR decision-making support tool, a case study is performed at the Dutch Railway company NS. Participants of the research are all operators in NS and were selected based on their expert knowledge and expertise in maintenance operations. This ensures insights gathered are representative of the target population and contribute to the research objectives. In total, 14 troubleshooting experts are available to participate in the research.

4.4.1. Interview and workshop sessions set up

In total two interviews and one workshop session are organized: (1) an introductory meeting, (2) positioning design and establishing a research approach, and (3) a real-life scenario setup. These sessions are organized to engage, gain in-depth knowledge, and share visions with the workforce community in developing future decision-making tools. Besides this, the interview and work sessions are used to set up the requirements for the configuration backbone of the AR tool.

Semi-structured interviews are used to specify the initial questions, followed by questions in response to the interviewee’s answers, enabling the interviewer to delve deeper into specific topics. This approach fosters an organic exchange of information and facilitates a comprehensive exploration of the research. In total, 14 questions are formulated based on three categories: (1) data availability and accessibility, (2) missing and required data and (3) usage of a centralized data platform. The categories of questions used in the interview are linked to the themes and findings identified in the state-of-the-art. This ensures that the interview questions are informed by existing research and address relevant topics within the field. Constraints and opportunities related to the data infrastructure are drawn from the analysis.

After the first interview, a plan of approach is drawn up, building a clear research approach and strategy. A case study is proposed to gain in-depth insights into real-world phenomena and exploration of complex issues within their natural context, making them particularly well-suited for investigating the practical application of AR and decision-making. The case study is further explored and a follow-up interview examines the relevance of AR to existing work practices. Participants are asked to provide information on current decision-making strategies, and potential AR application fields within their work procedures and distinguish relevant and useful data.

During the interviews and workshop, the researcher takes notes, observes participants, and poses counterquestions based on the participant's reflections. Observations focus on how operators carry out maintenance work, their reactions to contradictory or inconsistent data, and their perceptions of the potential for AR technology in troubleshooting complex problems. By actively observing participant reactions and behaviours, insights are gained into the practical challenges faced by operators and the specific areas where AR tools could offer support. The results are shared and discussed with the interviewee afterwards. To systematically process the unstructured data, ATLAS.ti is used [45]. Open coding procedures are then applied to the data, allowing for the development and modification of codes as patterns and themes emerge during the coding process. This iterative approach to coding ensures flexibility and adaptability in capturing the complexity of the data and facilitates the exploration of various perspectives and interpretations.

4.4.2. Case study setup

A real-life rolling stock failure is analysed to examine the current troubleshooting and decision-making procedure. Focus is put on the Verlengd InterRegio Materieel (VIRM-m1), a refurbished double-decker rolling stock series, built between 1994 and 2009 and refurbished starting in 2015 [107].

Based on the requirements, opportunities, and constraints that emerge from the interviews and workshop sessions, the configuration backbone of the tool can be formulated. Figure 4.3 represents the flowchart of the AR decision-making tool. The first step is to identify the decision-making process involved in troubleshooting and maintenance tasks within the railway industry. This includes understanding the sequence of steps taken by operators to diagnose faults, determine appropriate actions, and implement solutions. Next, existing procedures and workflows for troubleshooting and maintenance are analyzed to identify key decision points and potential areas for improvement. This involves reviewing documentation, interviewing operators, and observing maintenance activities in action. Decision paths are mapped to illustrate the various routes available to operators at critical decision points, where informed decisions must be made based on available information. The flowchart is then enhanced to incorporate AR functionality, including features such as real-time data visualization, interactive overlays, and guided troubleshooting instructions. The flowchart undergoes iterative design and testing to refine its usability and effectiveness. AR will play a significant role in consequently visualizing, guiding, assisting operators in their decision-making, and tracking the maintenance activities.

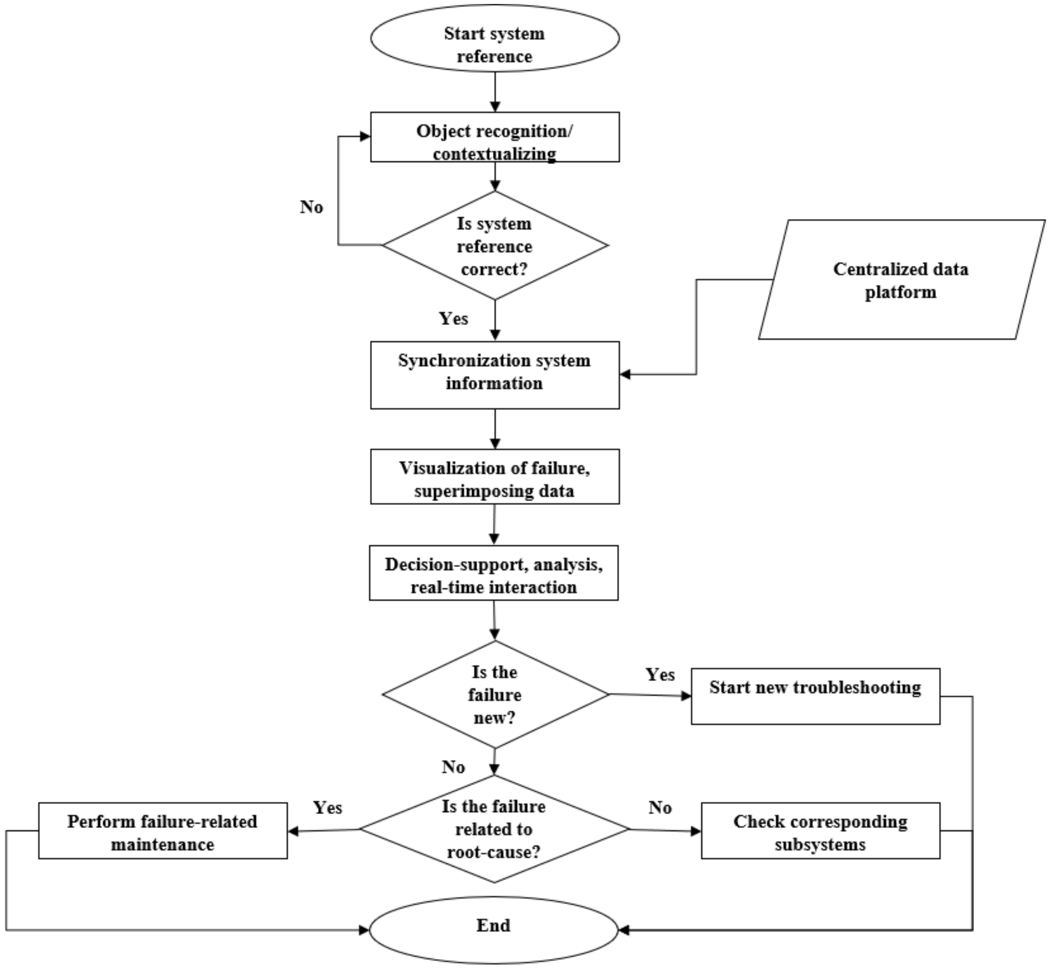

Figure 4.3. Flowchart of the AR decision-making tool.

Not only the decision-making and troubleshooting procedures are analysed, but also the entire IT infrastructure (data platform) in terms of data collection, availability, and structure. Once the configuration backbone is developed, requirements are set for the case study and the AR decision-making tool. The AR decision-making tool is based on what-if scenario reasoning to construct associations between the failing object and the input data to provide the operator with troubleshooting directions.

First, the basic implications of the what-if analysis are described for the inspection, analysis, and maintenance phase of a troubleshooting procedure by the operator. To model the what-if analysis branches, edits, and integrations are proposed. A branch represents the list of failures gathered based on historical data. New failures are beyond the scope of the study. The edits include each maintenance task executed by the operator. An integration connects the rolling stock failure to the corresponding maintenance task to be executed. The what-if analysis is based on the company's existing Failure Modes and Effects Analysis (FMEA) and Fault Tree Analysis (FTA).

4.5 Configuration backbone

The configuration backbone is a result of an analysis of the interviews and workshop sessions. Based on this, a configuration is set up with directions on which a case study will be applied.

4.5.1. Analysis of interviews and workshop session

From the interview sessions, it appeared that operators have a high interest in making use of a centralized data platform in which all relevant information is stored, record and store data automatically, and present real-time data on failing systems. Based on a statistical analysis performed by maintenance engineers of the company, it appeared that the Controller Area Network (CAN) system fails often and is seen by operators as a complex IT/OT system. The CAN system is a communication system widely used for data transmission in different applications as in the automotive and aircraft sectors. Malfunctioning of the CAN system causes the rolling stock to be withdrawn from operations for up to 3 days. Current corrective maintenance is based on a trial-and-error troubleshooting procedure. Multiple subsystems are connected to the CAN which causes a collection of failures which are: the sanitary system, climate system, camera security system, lights, and low-voltage system. From these subsystems, sanitary system failure is very common and has a high impact on rolling stock operations.

Operators state that sanitary failures are often not resolved correctly, causing an accumulation of system failures and forcing the rolling stock to be taken out of service. Therefore, the sanitary subsystem is thoroughly analysed. Also, the operators consider exploiting the sanitary system as an appropriate use case that adds value to their current troubleshooting method.

4.5.2. Configuration directions

Operators indicate that they carry out maintenance work based on their training, instructions, knowledge and expertise. Contradicting, not up-to-date, and inconsistent data is given to operators. The operators see great potential for the use of AR by visualizing FTAs, enabling video recordings of maintenance actions, presenting real-life system information, providing remote support, and troubleshooting complex problems.

Possibilities emerge to guide operators through their complex decision-making strategies by using FTAs and what-if analysis for troubleshooting directions using an AR tool. This is based on existing company FTAs which are supplemented and corrected by the knowledge and expertise of the operator. New FTAs are created and connected to a centralized data platform, which stores and structures all failure and maintenance-related data. All possible failures are analysed and connected to the correct maintenance task execution. More specifically, the operator answers system failure-related questions in AR to determine the root cause of the problem. Troubleshooting new type of failures are out of scope.

The combination of visualizing data from IT/OT systems with object recognition helps operators to make clear system references and thereby understand localization of the complex failures. To achieve this, data should be collected, filtered, and structured.

Given the boundary conditions and the requirements of the AR decision-making tool, a new database will be developed in Microsoft Azure. The AR UI design is developed in game design software Unity and visualizations are presented in the Microsoft HoloLens 2.

4.6 Case study: sanitary system VIRM

The goal of the case is to develop a prototype AR tool aimed at capturing real-life system conditions, understanding troubleshooting activities, facilitating problem-solving decisions, and tracking maintenance actions. However, before AR can be used for decision-making, data needs to be collected, filtered, and structured. In this research, a centralized data platform is developed to collect, filter, and structure all rolling stock data, such as real-time system data and maintenance data (see Figure 4.3). In this way, AR technology can easily visualise real-life system data. Based on existing FMEA and FTA, what-if analysis is proposed for troubleshooting. To indicate which maintenance instructions should be performed on the failed component, object recognition is used. The goals of the case study are threefold: (1) create a centralized data platform, (2) use object recognition to detect the system and use AR to visualize structured information of the problem, and (3) support the operator in decision-making.

There are multiple sanitary failures, however, the sanitary failure related to the pipe temperature in the toilet is identified as being the most appropriate IT/OT complex system that validates AR decision-support tools. This failure depends on the bioreactor interface, the toilet, and the temperature sensors in both systems. When this failure occurs multiple causes can be identified, such as invalid notifications, a clogged toilet, general toilet failure, and low pipe temperature. Subcomponents are collected from the rolling stock and connected in the laboratory for simulation purposes. To simulate this failure notification, all relevant failure sensor data is collected from the rolling stock and displayed in a laboratory environment.

4.6.1. Centralized data platform

Developing an AR decision-making tool requires connecting all data information sources to the corresponding operational phase. Troubleshooting is facilitated by visualizing information and eventually enables dynamic decision-making which is presented in Figure 4.4.

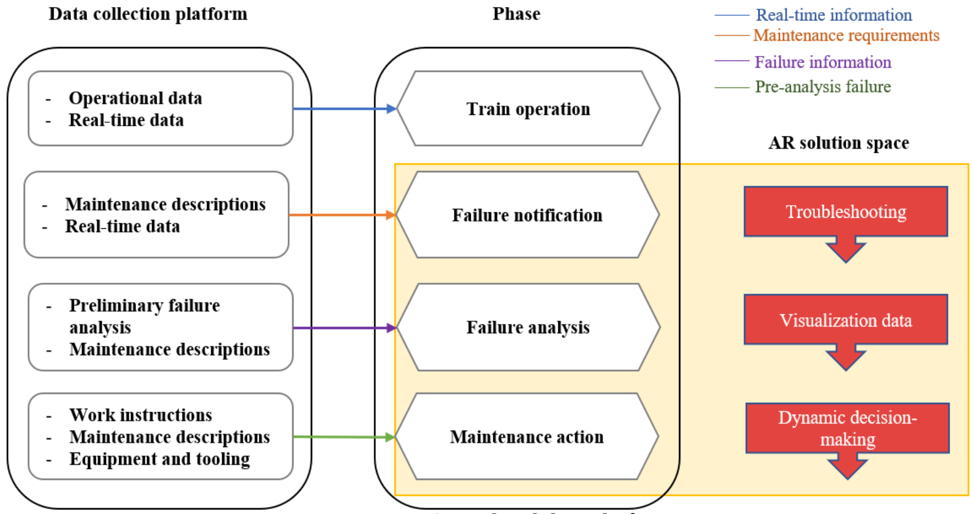

Figure 4.4. Centralized data platform.

Troubleshooting failures requires using data from multiple sources, all having different structures and content. Sanitary data is collected, filtered, and structured in a centralized platform. The centralized data platform is a collection of direct output coming from an organization. Centralizing data has the benefit that accessibility provides an overview and connects the correct filtered data to the distinguished operational phase. The AR solution space focuses on a specific rolling stock failure, with subsequent analysis to get to the root cause of the problem. After a thorough analysis is done, a maintenance action is performed. The AR decision-making tool thereby supports in troubleshooting, visualizing data and eventually supporting operators in decision-making.

For sanitary failure, information is collected from real-time monitoring data, work instructions, work order history, tooling and equipment, current troubleshooting documentation, and maintenance instructions. Data related to the failure notifications, failure analysis, and maintenance action are connected using FMEA and FTA for troubleshooting. Hereafter, maintenance tasks are visualized in AR.

4.6.2. Initializing AR decision-making tool

The given error code regarding the bioreactor of the sanitary system generates multiple diagnoses and corresponding maintenance actions. Table 4.1 presents the percentage of occurrence of the failure code for each diagnosis.

Table 4.1. Diagnosis error code and its occurrence.

Diagnosis	**Percentage of occurrence [%]**
No proper diagnosis is available	26
Toilet full	16
Multiple error codes present	11
No frost protection is available	13
Software bug	6
Physical error	17
Sensor failure	11

The AR decision-making tool is based on the percentage that a certain failure occurs. When a new error occurs, the operator runs through an FTA checklist in AR to see what diagnosis can be drawn from the new error. Simultaneously, object recognition will provide corresponding system information. Based on the diagnosis, the associated maintenance actions are presented in AR. The operator will be guided through the entire process to complete the task. After completion of the task, maintenance records, such as the maintenance task and time required for execution, will be stored in the centralized data platform. By recording maintenance activities and the time required for them, a new FTA can be developed in AR by automatically adjusting failure occurrence rates. Moreover, maintenance planning can be adjusted based on this data.

4.6.3. AR decision-making tool setup

The HoloLens 2 is used as an end tool to recognize the object, present maintenance solutions and enable dynamic decision-making. The four main components required to develop the AR tool are (1) a centralized data platform, including (geometric) system information, (2) information visualizations, (3) system reference, and (4) presenting the AR solution to the user. Figure 4.5 presents an overview of the setup of the AR decision-making tool. The centralized data platform contains all data coming from maintenance operations and procedures and is input for AR visualizations and system reference. The system reference ensures object recognition to provide system information to the operator. Visualizations are presented in AR and based on maintenance and failure data. All information is presented in an AR environment to the user and the system can record and track the maintenance task and feed the centralized data platform with this new information.

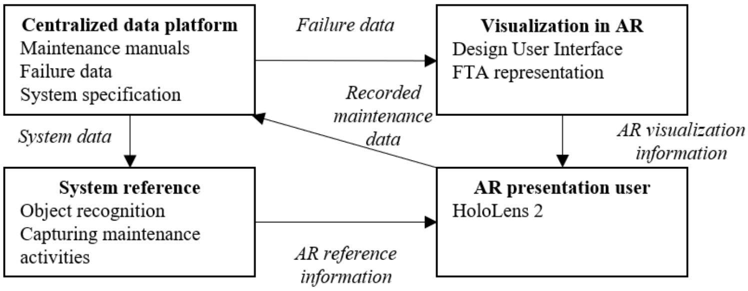

Figure 4.5. Set up AR decision-making demonstrator.

An AR database is generated in SQL Server Management Studio (SSMS). A new Azure SQL database is created to store, filter, and structure all failure data and maintenance documents. This database is needed to access required failure data and maintenance procedure data visualized in AR. The SQL server connects to Unity for immediate representation and augmentation of data. The system reference can be presented using object recognition and is implemented using the Vuforia Engine Package. Object recognition identifies and locates the distinct system components, different images are given as input for object detection. Standardized work descriptions, work orders, and maintenance manuals are derived from the centralized database and visualizations are developed in Unity and presented in the HoloLens 2. The AR tool captures real-time activities and decisions made by the operator. The four main components can be created and designed simultaneously by developers.

4.7 Results

The AR decision-making tool consists of multiple steps which are represented in Figure 4.6. The AR decision-making tool receives processed information from the SQL server. The operator can either continue previous maintenance activities or start a new maintenance activity session. By using object recognition, the tool can make a system reference and generate real-life system specifications from the centralized data platform. Simultaneously, a list of failures related to the sanitary system or the CAN bus is presented (see Table 4.1). From this, associated maintenance actions are presented.

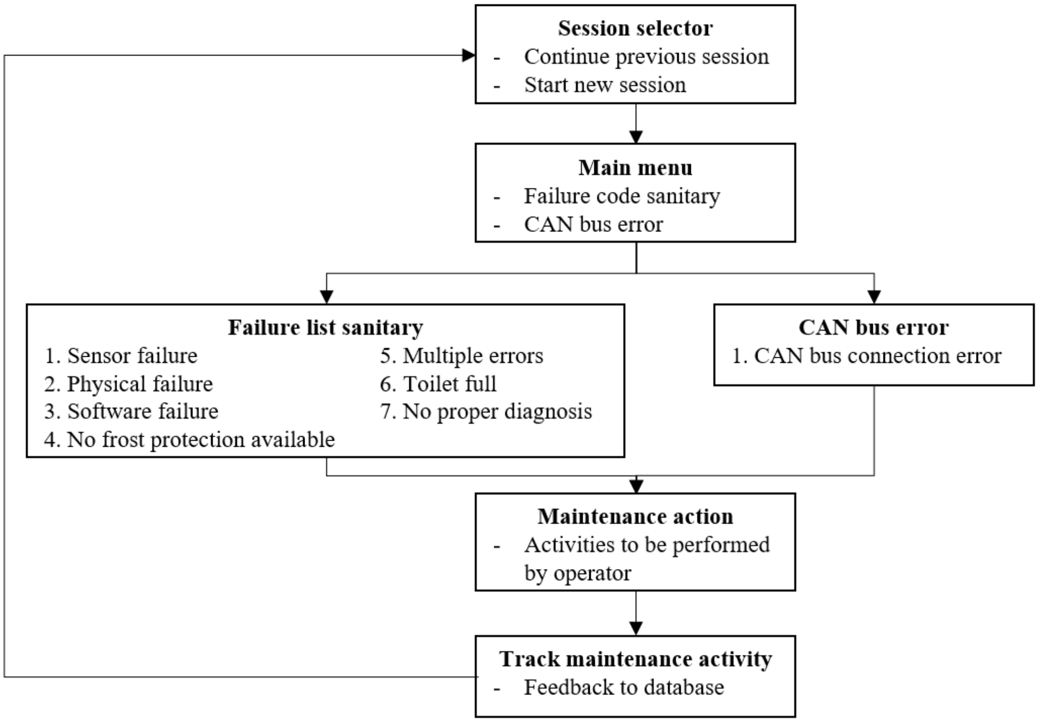

Figure 4.6. AR decision-making tool sanitary system VIRM.

The operator will be guided through the activities employing a what-if-analysis checklist. If maintenance activities are not completed, the operator can pause the session or go back to the initial main menu to explore different root causes. In case the maintenance activity is completed, the system records the time and activities performed to solve the system failure. The SQL server adds new data to the platform automatically and the percentage of failure occurrence is adapted to the performed action.

4.8 Conclusions and future work

This chapter presents the development of an AR decision-making tool to support maintenance operators in their troubleshooting work. The novelty of the created tool can give combined decision-making support to operators by (1) extracting, filtering, structuring, and translating data and relevant information from a centralized data platform, (2) capturing real-life system information using object recognition, (3) presenting troubleshooting directions using a what-if-analysis, and (4) tracking activities to develop future maintenance operations. AR is a suitable visualization technique because of its combined capabilities of contextualization, spatial mapping and providing real-time information to the operator. The tool provides a clear overview of a complex IT/OT rolling stock failure. This study takes into account the limitations set by operators in troubleshooting activities. Additionally, the tool enables a problem-solving strategy that uses data exchange from a centralized data extraction platform.

Future work on similar applications could focus on an extension of the same approach to cover the limitations of this study. Finally, the application will also be tested in real-life maintenance operations to analyse the limitations of the current laboratory setting.

Chapter 5 – Troubleshooting: a dynamic solution for achieving reliable fault detection by combining augmented reality and machine learning

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Changes: This chapter is translated from United States to British English.

5.1 Theme III: Backbone for AR troubleshooting: Front-end and back-end

This chapter is crucial as it addresses the contemporary challenges of complex maintenance operations and the overwhelming influx of real-time data, highlighting the need for innovative solutions (Figure 5.1).

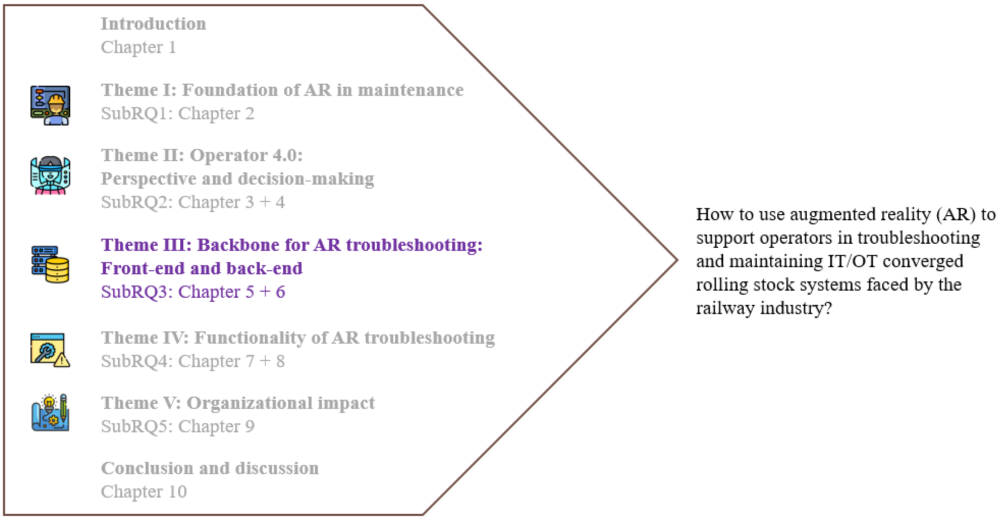

Figure 5.1. Theme III: Backbone for AR troubleshooting: Front-end and back-end.

Today's perplexing maintenance operations and rapid technology development require an understanding of the complex working environment and processing of dynamic and real-time information. However, the environment complexity and an exponential increase in data volume create new challenges and demands and hence make troubleshooting extremely difficult. To overcome the previously mentioned issues and provide the operator with real-time access to fast-flowing information, this chapter proposes a hybrid solution made of AR further combined with ML software. In particular, a dynamic reference map of all the required modules and relations that connect ML with AR on an example of adaptive fault detection is presented. The proposed dynamic reference map is applied to a pilot case study for immediate validation. To highlight the effectiveness of the proposed solution, the more challenging task of measuring the impact of combining AR with ML for fault analysis on maintenance decisions is addressed.

5.2 Introduction

The increasing requirement for reliable, available, maintainable, and safe systems makes traditional maintenance strategies less effective and obsolete [14]. Due to the complexity of the systems and thus the maintenance procedures, in-depth knowledge is needed to detect and resolve failures. However, often the operator does not have this knowledge, and as a result, requires more support for troubleshooting.

Traditionally, the fault diagnosis is based on manual inspection of the machine's health state [108]. However, some maintenance tasks rely on many dependencies and relations with other assets and systems and are therefore too complex to be understood by the operator. In modern industrial applications are therefore automatic fault diagnosis methods required, able to recognize the health state of a machine and identify the causes of this state. Such an approach would enable the operator to diagnose failing components in an early stage and hence would make the production flow more effective and efficient.

The ongoing digital transformation of industrial environments and practices in the light of Industry 4.0 is a perfect scene for future automation. In this aspect, the open-ended development of AR can help in addressing increasing complexities in machinery, and provide remote maintenance, whereas AI and cloud/edge computing can help in the analysis of the collected extensive data sets to automatically diagnose the machine state, perform quality inspections and effectively predict the failure of the machine in advance. The use of the combination of AR and AI can further reduce maintenance costs and unexpected downtime [16].

In the context of Industry 4.0, both AR and AI have evolved independently, and are only recently studied in combination [109]. However, most of the existing research in this direction is limited to tasks such as detecting, localizing, and identifying objects by AI approaches in an AR environment [109]. To extend these research fields, AI can potentially be used as a tool in the AR software environment [109].

The literature includes applications of anomaly and structural damage detection for prognostic health monitoring [14]. However, the application of integrating AI with (AR) wearable computing technologies for predictive analytics should be explored further [14]. AI and AR are both individually likely to help advance troubleshooting complex failures and give the operator in-depth knowledge of the problem. The combination and integration of both have the potential to support this even further.

In this chapter, the focus is on the integration of the KBS [110], AI, and AR in new technology (see Figure 5.2 for schematic representation), that can be used as a tool for supporting troubleshooting. The role of the KBS is to incorporate the expert's knowledge, and the supporting information necessary for complex maintenance tasks on the operator side [110]. Then AI, in particular ML/deep learning (DL), is used to extract and analyse the desired information. Eventually, this technology element supports the operator by screening failure diagnosis and possible repair instruction. To close the information loop between KBS and AI, and hence contextualize and visualize context- and user-dependent information, the AR element is utilized. The three modules together define a dynamic reference map required to perform automatic fault diagnosis. In this way, all elements are related and connected and hence will be an important starting point for troubleshooting.

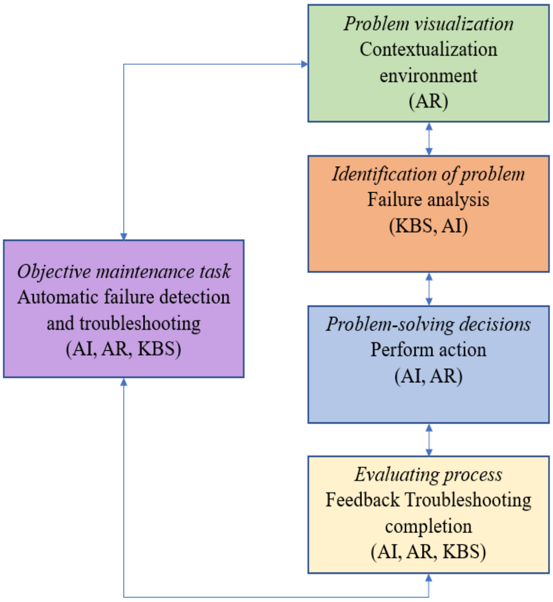

Figure 5.2. Relations between KBS, AI, and AR.

The chapter is organized as follows: a brief introduction to the KBS, AR and AI for troubleshooting is given in section 5.3. The technology foundation of the dynamic reference map and all its modules required to map the environment to the troubleshooting procedure are described. In section 5.4 a case study is analysed as an early-stage demonstrator. Finally, section 5.5 concludes the chapter and outlines topics for future research.

5.3 New dynamic reference map

The newly proposed dynamic reference map connecting KBS, AI, and AR modules for automatic fault detection is depicted in Figure 5.3 by adapting the KBS architecture presented in [110].

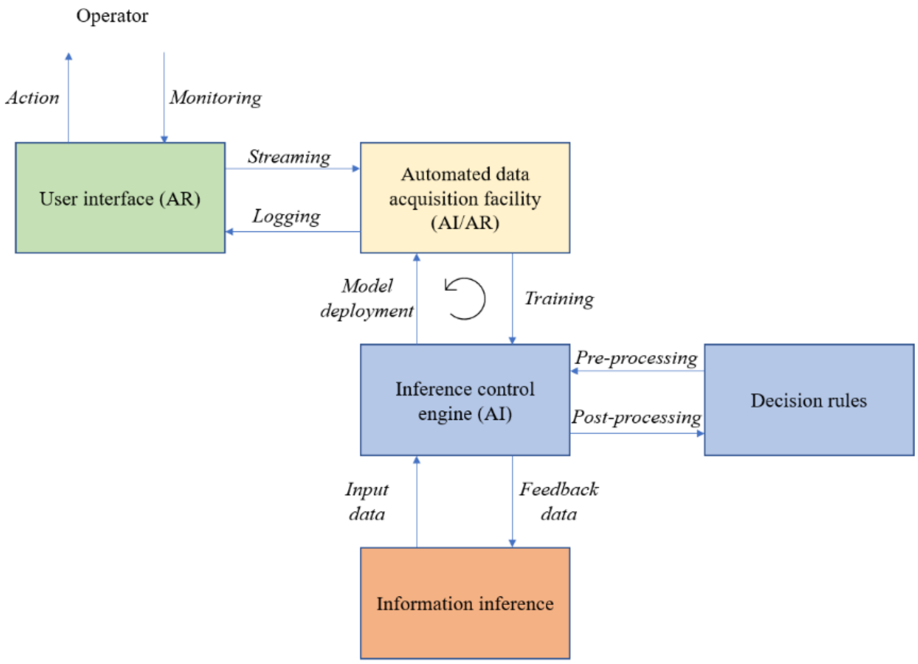

Figure 5.3. Dynamic reference map.

5.3.1. *Initializing reference map*

The map starts with the AR UI that simply ensures efficient communication with the user through menus while having a clear graphical UI that contextualizes, visualizes, and provides real-time information to the operator. This interface is then coupled to an automated data acquisition facility which transfers real-time data captured by the operator, its problem-solving expertise, and/or other information sources to an AI module. Since AI is capable enough to recognize, classify and predict the expected health state of a machine, this module is also referred to as an inference control engine [111]. This module acts as the brain of the system that uses the rule interpreter to execute a forward chaining algorithm and selects a methodology for reasoning. Next to the acquisition data, the control engine also uses data available in the information inference source, where the knowledge needed for understanding maintenance, in the form of manuals, figures, videos, and documents is stored. Finally, the decision rule module detects if additional data are required. Hence, the inference control engine uses input data and decision rules to automatically diagnose a failure and identify the corresponding maintenance tasks with the help of the appropriate ML/DL model. Failure diagnostics are then reported to the UI and the operator is provided with maintenance tasks required to resolve the fault.

5.3.2. *Technology foundation*

The novelty of this research is based on combining AR spatial mapping with the processing power of AI while visualizing the results directly in AR. Data is collected from the KBS to supply supportive information. When these modules are connected, one may trace whether the operator understands the real-time information or not, by comparing performed activities with the suggested or expected activities. Similarly, monitoring maintenance activities, as well as capturing outcomes becomes possible. These data can be further used to improve the AI system for future maintenance activities. Eventually, connecting KBS, AI, and AR releases the contribution of human labor and automatically recognizes the health state of a machine.

5.3.3. KBS module

Maintenance operators are mostly experts in the field and have specific domain knowledge that consists of experience, expertise, judgement, and the knowledge about methods required to solve complex maintenance problems.

Capturing and formalizing the previously described knowledge is the main focus within the information inference stage, which applies logical rules to the knowledge base to deduce the new information that can directly be used in maintenance operations [112]. When maintenance procedures are standardized, reliability prediction information can be collected and used as input data for information inference. From the standardized procedures, requirements and boundary conditions can be set. However, when procedures are standardized, the support given to the operator will not be dynamic. Therefore, the information inference requires the user to continuously feed the system with new data. When a service task or fault diagnosis is resolved, the operator must replenish the information inference with new information. Hence, this new information supports the maintenance procedure in establishing new strategies. To conclude, the information inference must be synthesized after every task performed by the troubleshooting tool.

5.3.4. AR module

The AR module in the proposed dynamic reference map can successfully assist maintenance operators in improving their overall productivity by corresponding automatic object recognitions and inspection of the machine or its parts. Similarly, maintenance tasks can be visualized and screened according to the failure diagnostics. This is achieved by visualization and contextualization of data stored in an intelligent data acquisition facility, a link to the AI module, that couples the maintenance instructions, the maintenance information systems, and the environment together. Data captured in the intelligent acquisition facility help the operator diagnose faults correctly, by e.g. showing only the appropriate information which is normally not visible without AR. Therefore, the readability of text instructions in AR should be sufficient and simplified. Furthermore, the use of visual elements is partially encouraged [113] by translating as many text instructions to (2D or 3D) graphic symbols, if possible. When maintenance information is supplied properly to the operator and feedback on data is acquired, proper failure diagnosis and repair can be guaranteed. However, to make use of AR solutions in different applications, the new authoring manuals for automatic failure diagnosis have to be within Industry 4.0

principles [114]. This offers structured and real-time communication by using automated augmentation of message elements and improves efficiency in terms of time and error reduction. Next to this, standardized communication between CPS, the operators, and the environment is desired. Similarly, the performance data collected during diagnosing and repairing operations, have to be marked, tracked and captured for further improvements of the system. Hence, the AR module has to provide a digital and contextualized version of technical documentation, exchange real-time information, and be highly flexible. To achieve this, the specific hardware-software choice for the AR module has to be made based on the user and maintenance requirements [115]. Any hardware solution that interacts with human senses (e.g. tablets, Head Mounted Displays (HMD), Hand-Held Devices (HHD), projectors, and headphones) can be an option. Based on the desired quality, resolution and environmental conditions, these can be marker-less or marker-based AR systems [114]. The decisions on when, how and which type of AR can be used highly depends on the clarity of existing information on the operation application, specific maintenance tasks, and the end-user [116]. This decision can be made throughout the development and use phase since standardized communication allows multiple AR solutions to fit the system, and to be changed over time.

5.3.5. AI module

Over the years, an increasing amount of data is gathered from machines leading to more useable diagnosis results. To automatically learn features given the input monitoring data and hence recognize the health state of machines [111], one can use the inference control engine (AI module). Inference control engines can be classified into four categories: (1) rule-based reasoning, (2) fuzzy-logic-based reasoning, (3) ML/DL-based reasoning, and (4) case-based reasoning [111]. In the case of ML/DL reasoning, the correct workflow in intelligent maintenance operations and the adequateness of decision rules highly depend on the accuracy and prediction of ML/DL models [117]. To diagnose failures of the tracked equipment and/or component, the appropriate ML/DL model, as well as, the dataset of sufficient size and quality have to be identified. Therefore, sensible decisions on the collected data type and handling are required. For example in predictive maintenance based on ML/DL approach, large datasets are required. This is often not feasible as the data are often not available in the public domain [117], or not collected at all. Although real-time data is preferred over laboratory data, the latter are more often used due to their availability. The main challenge is, however, that these datasets do not contain disturbing features or records of subcomponents of the machine [117].

The choice and optimality of a suitable ML/DL model on the other hand depend on the chosen AR module, which is to be complemented by AI. In general, ML/DL models are used for image classification and object detection given the data collected by the AR module [109]. Image classification, as a predecessor to object detection, recognizes the scene and labels it to the corresponding class. Furthermore, object detection is used to recognize the objects in the scene by for example bounding box method or similar. Besides the mentioned AI applications in AR, the inference control engine also captures the performed tasks.

To develop a decision-making engine, DL can be deployed for big data scenarios. ML/DL-based diagnosis procedures consist of two steps: (1) big data collection and (2) automatic diagnosis [111]. Once the dataset is collected, the manually extracted data features [111] are mapped to the corresponding failure class via classical ML models [16]. However, this type of modelling requires complicated feature engineering in contrast to the DL approach. Following this, the main objective of the inference control engine is to identify the optimal supervised, semi-supervised or unsupervised ML/DL model within a defined computational timeframe. Utilizing the results from the ML algorithm requires special interpretations [109] that depend on the characteristics of the dataset, the chosen algorithm, the parameter setting, and the expected output [109].

For effective maintenance interventions, discernment in the model's interpretability, explainability, and accuracy is of the utmost importance. Hence, the model verification and validation have to be analysed according to the preset objectives.

Finally, the outcome of the inference control engine provides machine diagnostics for the operator. Consequently, when combining KBS, AI, and AR, a new maintenance strategy can be established to support the operator.

5.4 Real application troubleshooting

To enhance the knowledge and understanding of the process behind the reference map, a case study is executed. To validate the dynamic reference map, the proposed process is implemented in an early-stage demonstrator. Eventually, a questionnaire is employed to reflect on the case study.

5.4.1. Case study

The case study comprises automatic failure detection, which combines KBS, AI, and AR for troubleshooting. The case has been selected based on the data given by diagnosis experts from a machine manufacturing company. These modular machines produce lay-flat photobooks and other premium print-on-demand products.

The company provided over 20 hours of interviews to identify current processes and solutions in the classification of well-produced book blocks. Based on the interviews, a FMEA was performed and revealed that the book spine is mostly printed incorrectly [118]. More specifically, when the moving table and the rotating drum are not aligned, the book spines are not produced correctly.

A book spine is classified as good or bad and is bad if: (1) the book spine is uniformly leaning, (2) the book spine is one-sided leaning, (3) the book spine has a bulbous shape, or (4) the book spine has a hollow shape.

5.4.2. *Early-stage demonstrator*

The troubleshooting demonstrator comprises three main components: (1) an information inference to store the transferred data, (2) an HMD for the operator with an AR application using the HoloLens 2, and (3) the AI intelligent control engine. The system overview, along with the software and hardware is presented in Figure 5.4.

For information inference, interviews are performed with operators. Besides this, operating manuals, maintenance instructions, notes, videos, images, and CAD files of the machine are structured and stored. As access to the real-time data from the machine was not available, images of badly produced book blocks were collected.

To identify the appropriate maintenance task, the image of the book block has to be classified appropriately. To achieve this, the convolutional neural networks (CNN) are offline trained on a balanced dataset of bad and good book spines and further used for online classification.

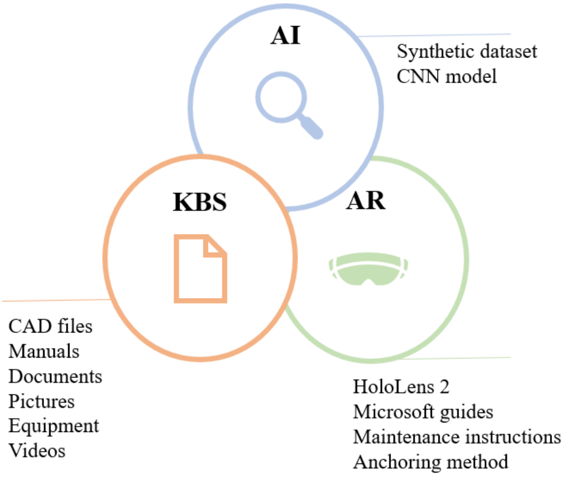

Figure 5.4. System overview.

Due to the limited dataset, 100 images of real book blocks are augmented by a synthetic virtually emulated dataset. This results in a dataset consisting of 1000 images of both bad and good-produced books which can be classified into the five aforementioned classes.

Once the CNN model is trained, it is used on the real-time data coming from the camera stream of AR. The inference engine classifies the seen book block images by identification of the book spine problem. Images are recognized, analysed, and then used for predicting the correct label. Thus, the algorithm classifies whether the book spine is correct, uniformly leaning, one-sided leaning, hollow, or bulbous shaped. The predicted labels are then projected to the HMD.

Once the book block is classified, the corresponding result, as well as maintenance activity, is visualized on HMD based on the maintenance requirements. Maintenance of the considered machine is a standard operation performed by the operator. It is an operation of high occurrence and of very low variance in terms of time and maintenance failure rate. However, the machine itself is subject to degradation and hence may lead to a new maintenance operation. According to this, the maintenance (manual) instructions are generated in the information inference system, translated into the digital system, and anchored by a marker-based technology. To visualize the maintenance instructions on the HMD, Microsoft Guides is utilized. This application shows clear instructions while still being able to use custom pictures, videos, text, and 3D models.

In short, a DL algorithm can classify good and
wrong book spines, label the specific failure, and display the results on the HMD. Hereafter, the maintenance steps used to solve the issue causing the book spine problem are visualized on the HMD.

5.4.3. Feedback on the proposed process

The proposed dynamic map is validated by questionnaires. Expert and non-expert operators' feedback is gathered, recorded, and compared. In total, six participants took part in validating the process. Participants were selected based on their level of expertise ranging from no previous experience to good knowledge about the HMD.

All participants were asked to detect, inspect, and recognize a wrongly produced book spine. Hereafter, the DL algorithm and HMD are used to provide failure information and the corresponding maintenance task to the operator.

The goal of this validation process is to identify (1) the usefulness of the reference map, (2) the problem-solving capabilities of an automatic failure diagnosis tool, (3) the reduction of diagnosis failures, and (4) the effect on maintenance operations in terms of time. To score the previous statements, participants were asked about their experience and the level of satisfaction related to the aforementioned four goals. Statements are ranked between 1-5 in which the score varies from strongly disagree to strongly agree. Table 5.1 presents the results of the validation session.

Table 5.1. Validation session automatic failure detection.

Validated item	**Average score**
Usefulness	3.5
Problem identification capability	4
Time	4.2
Failure reduction	4

As the collected dataset is limited, the corresponding statistical analysis is not provided. Instead, the information gathered during this experiment is used to make the first qualitative estimation of integrated KBS, AI, and AR structure and elements.

The data reveal that the majority of the participants were excited about using the troubleshooting demonstrator. Finding failures was easier when using automatic failure analysis by AI, and the use of AR guidance made the maintenance instruction clearer. Hence, the errors in the process were significantly reduced, and non-expert users felt confident when using the new technology. In addition, the experiment has validated the DL model used for the classification of both good and bad book spines. However, the classification procedure of the book itself was not as smooth as expected. Due to special features of the training dataset, the correct distance between the book and the HoloLens 2 was difficult to find so that the algorithm could recognize the book block and properly classify its state. To improve this, more attention should be paid to image classification in the future.

5.5 Conclusion

In this work, a dynamic reference map of all the modules required to perform automatic fault diagnosis is presented. The reference map describes the connection between KBS, AR, and AI in an existing maintenance system. The AI module is integrated as a computational system that automatically classifies and identifies failures. The AR module assists the operator in solving the previously identified failure. Thus, the given proposal draws a holistic view of integrating different modules to support the operator in his maintenance work, i.e. to supplement maintenance operations and contribute to knowledge enhancement by utilizing this troubleshooting tool.

A case study revealed that the dynamic reference map is rather accurate when relating KBS, AI, and AR to maintenance systems. Although most user reactions to the proposed solution for troubleshooting were positive, more attention needs to be paid to its direct application. This research has an impact on an organization's data infrastructure, i.e. data capturing and management. The AR module is connected to a centralized AI system for real-time data streaming. Identifying data processing techniques and developing centralized information management systems is required. Follow-up research is needed to develop the ML/DL algorithm with in-depth network and dataset specification. CNN promises efficient offline training of a balanced synthetic dataset, however, this dataset should be replaced by a dataset containing real images for online training and classification.

The current study is focused on image classification and performing maintenance on a physical component. Exploring the usefulness of this method in a different setting, such as maintaining digital systems, is also worthwhile. Thereby, adapting the algorithm to a big environment. Similarly, the dynamic reference map should be explored more thoroughly in different AI, and AR-model environments.

While the current research is focused on image classification, the next step is to include object recognition and detection.

In the future, this research should extend to creating a self-learning system that captures and transfers data to improve its capabilities. Thereby, a self-learning automatic fault diagnosis solution can be created that supports operators in their complex maintenance activities.

Chapter 6 – Augmented reality database architecture: the backbone for IT/OT train maintenance

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6.1 Theme III: Backbone for AR troubleshooting: Front-end and back-end

Maintenance is an important aspect of the entire lifecycle of rolling stock. The existing maintenance of converged information and operational systems is complex, caused by various types of physical and digital equipment components and complicated data collection, structuring, and processing. The quality of maintenance is greatly affected by the knowledge and experience of maintenance operators with their data recording techniques to populate a database. This chapter holds substantial relevance as it delves into the back-end aspects of AR troubleshooting by developing an AR database architecture (Figure 6.1).

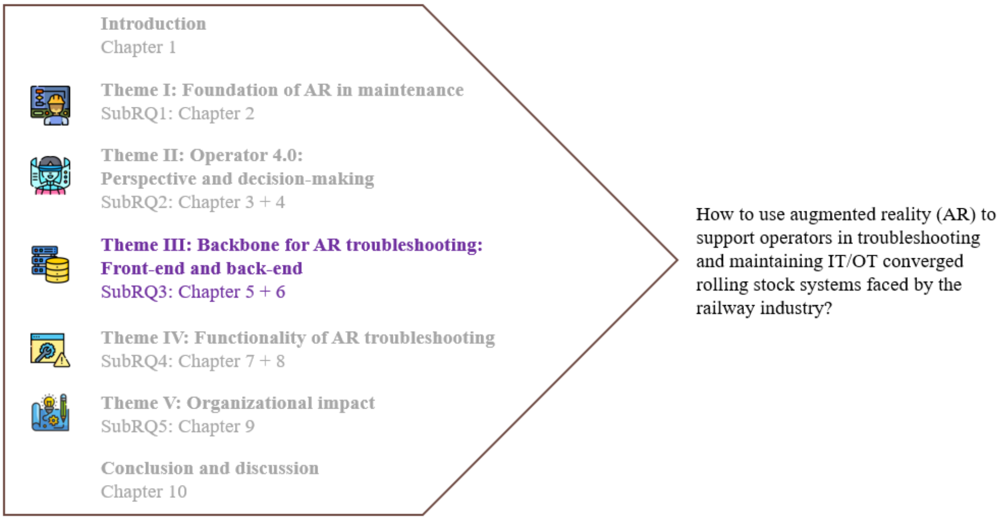


Figure 6.1. Theme III: Backbone for AR troubleshooting: Front-end and back-end.

Therefore, the goal of this research is to develop an AR database architecture to pre-process data for further use in data mining efforts to discover maintenance patterns and provide troubleshooting directions to facilitate operators with maintenance task execution information. Thus, providing intelligent assistance by generating refined information extraction on the IT/OT system failure. In this chapter, a real-life railway maintenance case study is investigated to validate the AR database architecture. Both manual data processing and NLP techniques are used to filter, categorize, and process data. PrefixSpan pattern mining is used to structure and visualize maintenance data that supports operators to identify the root-cause problem of a train failure. The work is evaluated using a cross-validation to identify challenges and opportunities related to the AR database architecture.

6.2 Introduction

The increasing complexity and automation of industrial machinery require new technologies for ensuring reliability and productivity through MRO operations [119]. In the railway industry, MRO operations costs can reach a significant proportion of the entire rolling stock lifecycle and even exceed the initial investment costs.

The modern rolling stock features many sensors and computer-driven equipment enabling self-sense, self-act, and internal communication. Real-time monitoring data can be obtained, shared, and combined with maintenance operations data to facilitate rapid, complete, and up-to-date system information. The connection and convergence of OT with IT are of key importance in the concept of CPS [120]. This convergence of IT/OT raises data complexity regarding data relationships and dependencies that cause largely unpredictable and involute failures [98]. Solving IT/OT failures requires access to available maintenance information, real-time data exchange, and the knowledge and expertise of operators. The expertise of operators strongly influences MRO operations by utilizing the troubleshooting procedure and completion time, thereby affecting MRO costs [121].

AR can help reduce errors in the troubleshooting strategy and completion time by allowing easy access to MRO information which today belongs mostly to the knowledge of expert operators [11]. Besides this, AR visualizes the data to identify and prioritize IT/OT failures and provide maintenance solutions [98]. Even though the advantages (time savings and error reductions) of AR have been proven by academics, the technology still lacks the robustness and flexibility in industrial application to become of common use [119]. Future work should focus on implementing AR technology in an industrial environment and the data infrastructure in terms of structure, preparation, and availability through deeper scientific research.

For integrating smart control in maintenance operations, the IoT, AI, and ML create major opportunities [122]. In maintenance scenarios, the operator benefits from an automatic method to shorten the maintenance cycle and improve the troubleshooting accuracy [123]. Using AI, the procedure of pre-processing data, feature extraction, and data mining discovers maintenance patterns automatically and recognizes the health state of machines [111]. Zheng et al. (2018) present smart manufacturing systems and showcases several key technologies and demonstrative scenarios [120]. They highlight the need for future work on AR-enabled real-time visibility of working machines. The AR interface displays the status of a machine and its processing behaviour through a visualized model in real-time with smart machine data [120]. Research on the back end of the data collection, data processing, requirements and boundary conditions is key.

ML techniques offer great accomplishments for power system fault diagnosis [124]. The main issue with ML techniques is the limited dataset which dictates the detection, classification, and localization of failures. Researchers use synthetic data in the research to achieve similar performance in the real-world scenario. To fully cope with the fluctuating behaviour of a system, it is essential to use real-world data.

The data-oriented paradigm has proven to be fundamental for the technological transformation process that characterizes Industry 4.0 [125]. New system architectures have been proposed to integrate digital technologies to use data for industrial innovations [126]. These system architectures are aimed at standardizing smart technologies to push the development and implementation but require a realization of applied industrial frameworks. Other work is focused on developing a Digital Twin (DT) operational architecture model to transmit and share real-time information to improve the ability to simulate and predict grid networks [127]. Related work focuses on virtualizing the development of manufacturing environments so that production engineers can better assess and control the introduction of machine tools, processes, or workflows, and support the scale-up of production from laboratory to industrial scale [128]. The main added value comes from merging the information-based paradigm with the synthetic environments that make the digital system reference the main enabler of a purposeful and efficient way of thinking about production environments in development. However, the DT architectures are too and mapping the physical entity is complex. To integrate DT and Industry 4.0 technologies, the purpose-driven information management and digital infrastructure should facilitate an up-to-date information flow and thereby support decision-making [129].

The goal is to have high reliability and near real-time transmission interaction between the physical and virtual space. The lack of database architectures that allow visualization of structured data via AR makes it impossible to map complex system failures comprehensively. Based on the review of the concept of related technological database architectures, the current research situation in complex IT/OT failures, and combining ML methods for maintenance pattern mining, an AR database architecture is proposed in this work.

The main challenge is devising an architecture compatible with CPS, ML, and case-based reasoning concepts and practices before using AR [122]. Therefore, the novelty of this work lies in the development of an AR database architecture to collect and structure data, extract features for further use in data mining processes, discover maintenance patterns, and thus troubleshoot complex IT/OT rolling stock failures. The AR database architecture includes the following five building blocks: (1) data acquisition unit, (2) feature extraction unit, (3) fault diagnosing unit, (4) fault prognosis unit, and (5) AR interaction unit.

First, the research positioning and detailed methodology are provided. Second, a description of the AR database architecture, including an explanation, requirements, and boundary conditions is offered. The validation of this work is shown by utilizing a real industrial case study application. Finally, the results are presented and show that there is a need to have an AR database capable of intensively pre-processing data, isolating failure parameters, discovering maintenance patterns and rules, and prognosis and determining an action to solve the failure that interacts between the database and the AR technology.

6.3 Methodology

The developed AR database architecture enables visualization of structured data using AR to identify and prioritize IT/OT failures and provide clear maintenance solutions. The architecture depicts what information should be processed and structured, how to troubleshoot, and how to use this information for future maintenance troubleshooting. In the following, the development method of the architecture and an industrial case study setup are presented, as they form the basis of this work. A schematic overview of the methodology is presented in Figure 6.2.

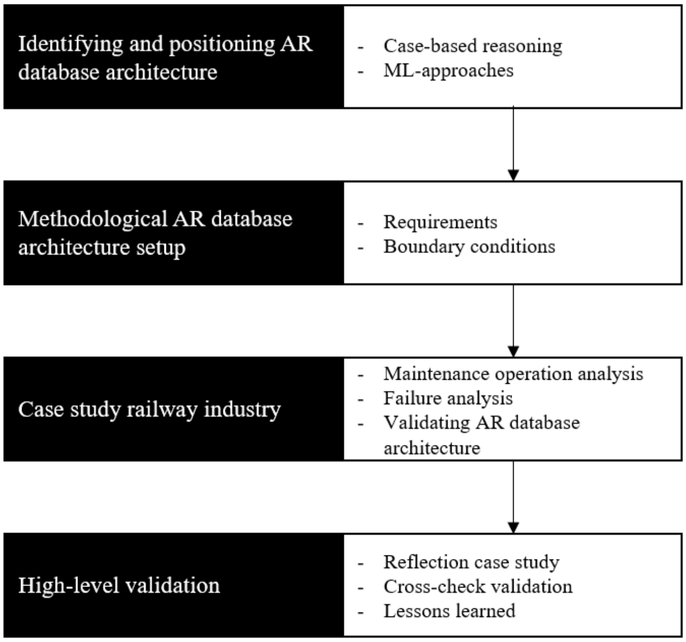


Figure 6.2. Schematic overview of the methodology.

6.3.1. Architecture development

Presenting the context in which this chapter is inserted is essential to justify the choice of the methods adopted. For this reason, the first part of this work focuses on identifying and positioning the AR database architecture in rolling stock maintenance operations. Understanding and justifying its position is important to claim the relevance of this chapter to (1) demonstrate the gap that exists in applied database architectures for AR technologies, and (2) identify patterns, methods, and application methods whose relevance is evident for this work.

The proposed methodological architecture is based on the following units: (1) data acquisition unit, (2) feature extraction unit, (3) fault diagnosis unit, (4) fault prognosis unit, and (5) AR interaction unit. Each unit in this hierarchy requires input from its predecessor and external input or control to perform its function. The proposed architecture is heavily based on AI techniques such as ML [130], root-cause analysis (RCA), and case-based reasoning [131]. However, this chapter aims to provide a generic holistic database architecture that would suit a wide range of ML techniques for current and future generations of ML methods connected with AR systems.

6.3.2. Framing the case study

The use of case studies is a recognized methodology for explaining and validating specific phenomena, and to deeply investigate new phenomena in real-life conditions [132]. The railway industry is changing significantly and advances in computer-based technology must be integrated to improve efficient, safe, and secure transportation services. The NS faces many IT/OT rolling stock failures and thereby offers a great opportunity to exploit a case study for AR database architecture validation [98]. Several information sources are used throughout the research such as interviews, managerial presentations, maintenance operations data, public, and internal documents.

The case study is determined based on multiple interviews with managers and operators. For this study, 14 operators are selected, and all require knowledge of data collection and maintenance operations to understand IT/OT rolling stock failures. Semi-structured interviews are used, focusing on obtaining in-depth information on data availability, accessibility, and the future use of a centralized data platform.

Operational rolling stock data is collected and used as input to the database architecture to be filtered, structured, analysed, and presented via AR. PrefixSpan and NLP are used to identify maintenance patterns to obtain a failure diagnosis. Hereafter, a problem-solving strategy can be proposed in AR. The AR database architecture is discussed, completed, and improved through operator input to increase the validity of the architecture.

6.4 AR database architecture design

The goal of the AR database architecture is to ensure CPS, ML approaches, and case-based reasoning concepts and practices are merged to use AR and support the operator in solving IT/OT complex failures. This goal contributes to both the social context by involving railway industry stakeholders and the knowledge context by encompassing the state-of-the-art developments of the literature in database architectures, AR, CPS, and ML. To design the AR database architecture, design science research (DSR) guidelines are applied [133]. Table 6.1 summarizes all the guidelines for the development and design of the proposed AR database architecture.

Table 6.1. DSR guidelines of the AR database architecture.

DSR guideline	Design objective
Guideline 1: Design as an artifact *Guideline 2: Problem relevance*	Collect initial requirements and boundary conditions from experts in the railway industry.
Guideline 3: Design evaluation *Guideline 6: Design as a search process*	Validate and improve the utility, quality, and efficacy of the database architecture with experts.
Guideline 4: Research contributions *Guideline 5: Research rigor*	Contribute to knowledge in database architectures, fault diagnosing, and maintenance operations.
Guideline 7: Communication of research	Showcasing the outcome

6.4.1. Positioning of the AR database architecture

The fault diagnosis process is mostly executed by manually inspecting the health states of machines, increasing the labour intensity and reducing the diagnosis accuracy caused by human error. Identifying the electronic failure and its location in machines is supported by advanced signal processing methods [134][135]. However, operators require expert knowledge in understanding signal diagnosing in engineering scenarios. To automatically recognize the health state of machines, modern industrial maintenance fault diagnosis methods need to interpret, visualize, and contextualize data. To deploy AR it is required to collect and preprocess data, contextualize and interpret information, discover failure patterns, and define fault prognostics. To meet the aforementioned functionalities, it is necessary to develop an AR database architecture.

The AR database architecture positions itself between the rolling stock operations and maintenance procedures, as presented in Figure 6.3. The AR database architecture interacts with different information sources: (1) real-time system input, (2) procedural input, (3) operator input, and (4) UI. Operator input represents data that is subject to documented expert knowledge that is not always present and may reduce the diagnosis accuracy [120]. Case-based reasoning attempts to solve new problems based on the solutions and operator knowledge of similar past problems. Previous research exploits case-based reasoning to incorporate fault diagnosis of rail turnout using compound distance methods and to fault diagnose locomotives using on-board messages [136][137]. Real-time system input is online operational rolling stock data giving both feedback and system failure information. Procedural input is offline maintenance information related to IT/OT rolling stock failures. The UI is a function-integrated interface, in which the operator can interact with the system about the data transmission and diagnosis results. AR offers a powerful tool for supplying the operator with contextualized and customized failure information [123]. Displaying location-dependent information in AR environments and providing an adaptable level of information is important to control the guidance level of AR overlay to the operator [138]. In addition, the operator validates the fault diagnosis with the initial problem definition by providing interface specifications to enable decision-making. The AR database architecture collects all data from the various information sources and updates them continuously.

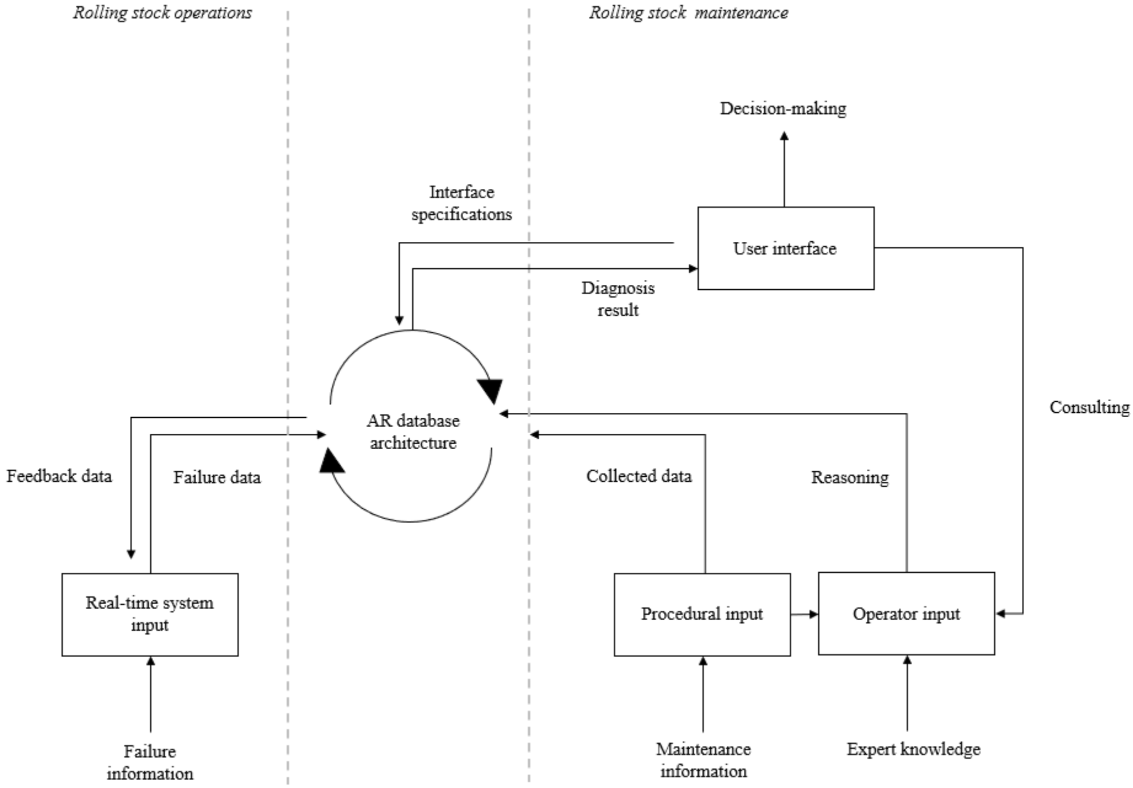


Figure 6.3. Expert system-based fault diagnosis model.

6.4.2. AR database requirements

Future maintenance operations involve collaborative human-AR interactions, hence the need for coordinating and monitoring maintenance processes with operators, technology, and rolling stock data. Seamless connectivity with automation solutions, smart technologies, and real-time data sources, is one of the most important design artefacts [139]. To maintain openness and modularity, the database architecture should offer a set of core functions and accommodate optional ones, with loose coupling between them. Table 6.2 outlines the functional requirements addressing the identified literature gaps.

Table 6.2. Functional requirements of the AR database architecture.

Category	Identified gap	Functional requirements
Database functionality and context	Current architectures filter information in an autarchic manner to stakeholders involved [128], but there is a need to make the architectures explicit.	Combining CPS, ML approaches, and case-based reasoning to display the information clearly through AR.
Data gathering	Models for collecting, ingesting, and presenting IT/OT data are currently focused on broad Industry 4.0 concepts and business logic [140].	Enable online and offline maintenance and IT/OT rolling stock failure data gathering by connecting physical systems, non-physical systems, and operators.
Data management	Data management strategies in the field of AR require a common data model for different applications and allow centralized and efficient management of data [141][142], integration into real-life scenarios requires further exploration.	With a predefined common model and data format, the architecture can store, organize, and maintain rolling stock, maintenance, and operator data while being compatible with AR.
Data handling	Diagnosis models can automatically present health information from the input monitoring data, which does not rely much on expert knowledge in feature extraction [111]. However, the operator influences data transmission, parameter configuration, result acquisition, and problem definition and consultation.	Creating a hybrid fault diagnosis model to learn features from operator input for discovering maintenance patterns to recognize rolling stock health status based on the learned features.
AR interaction	To maximize the advantage of AR concepts, an automatic and intelligent information extraction mechanism to present critical and relevant maintenance information is key [54]. Modelling, integration, and extracting efforts must be considered when building AR applications.	The database architecture provides a suitable AR interface to access information during maintenance procedures by interacting with maintenance execution and maintenance information systems to gain access to relevant data.

6.4.3. AR database boundary conditions

The boundary conditions for the AR database architecture are divided into four subgroups and established for both the human and technological side. To better understand reference database architectures, research from other industries is included.

Information access and exchange. The generation of a collaborative automotive troubleshooting planning architecture in modern automotive enterprises is presented in [143] and shows that troubleshooting not only involves complicated ICT systems; operators and enterprises are vital. Organizations collect maintenance and failure data, however, the data collected are usually redundant and incomplete. The AR database architecture has to exchange information promptly, thus enabling the operator to appropriate failure information. Furthermore, data management is essential to deal with knowledge of dynamic and unstructured data [143].

Human errors. As mentioned before, the AR database architecture highly depends on ML approaches, RCA, and case-based reasoning. However, maintenance operators influence giving the AR database architecture appropriate input data by documenting and structuring operational data. Operator input depends on their knowledge, expertise, and competence and is to be initialized through various data collection methods, such as interviews, on-the-job testing, empirical methods, and maintenance task simulations [76]. Research on information extraction for specialized domains mainly focuses on medical records [144]. Medical workers define the typical flow for the medical treatment of each disease and data input is based on the medical workers' experience. However, these human-based approaches are time-consuming and human errors are inevitable. Little research has been done on information extraction for the maintenance record domain [144].

Health state recognition. Assessing machine health can effectively ensure reliable and safe operation of rolling stock and provide technical support in decision-making about maintenance and repair. A pillar for combining condition-based maintenance and ML approaches is robust machine health state recognition [111]. Health state recognition is a method deploying ML-based diagnosis models to establish a relationship between the selected features and the health state of machines [111]. Diagnosis models are trained using labelled samples and then unlabelled samples are used to recognize the health state of machines. Through the AR database architecture, rolling stock failure information is visualized in AR and thus reflects on the health state.

Data processing. In the railway industry, a significant amount of data is stored in text format, where NLP and text mining techniques enable automatic feature extraction and discovery from such documents [145]. Converting unstructured text data is a complex process for which ML methods are appropriate [146]. Typical text classification tasks in the railway industry maintenance include identifying the root cause of the system failure by transferring textual data and classifying them into defined binary or multi-class labels [145]. Text classification supports maintenance pattern discovery and enhances work efficiency. Currently, however, human involvement in configuring and handling text data is still required for applied architectures. In the future, a process is desired to automatically extract the information from the text data.

6.4.4. AR database architecture building blocks

The AR database architecture is designed to enable flexible and simple data gathering and processing, fault diagnosis, and visualization. Convergence of online and offline data may require the integration of maintenance procedures with different levels of automation. Maintenance events must be easily shared across an organization. In response to the requirements (section 6.4.2) and boundary conditions (section 6.4.3), the proposed AR database architecture features data handling and fault diagnosing via AR, allowing entities in the platform to create a hybrid fault diagnosis model to (1) discover maintenance patterns, (2) recognize rolling stock health status, (3) troubleshoot IT/OT failures, and (4) visualize the problem-solving information.

Figure 6.4 depicts the five major building blocks (units) of the AR database architecture and the relationships between them. The main units are designed by rectangles, unit outcomes are designed by ovals and information flows are designed by continuous arrows. The architecture is implemented on an AR gateway and has five main units:

1. *Data acquisition unit:* data is collected from both online and offline environments which can be both real-time, operational, and historical data. All data entering the AR database architecture must be pre-processed before data characteristics can be extracted and fault specifications presented to the operator. Pre-processing of data involves spatial mapping for human-AR interaction and capturing operator feedback for knowledge sharing and documentation. The dataset is filtered to exclude, rearrange, or apport data according to predefined fault rules set by the designers. Filtered failure data is the result of the data acquisition unit. Data automation can be achieved through various techniques and technologies, such as workflow automation, integration platforms, ML and AI technologies, and data quality management.
2. *Feature extraction unit:* maintenance failure data is analysed to isolate failure parameters and characteristics. Ideally, this unit is based on ML methods and no human operators are involved. Based on this analysis, the current failure status with its specifications is obtained.
3. *Fault diagnosing unit:* intelligent fault diagnosis are ML theory that releases the contribution from human labour to automatically recognize the health state of the machines [111]. In the AR database architecture, the intelligent fault diagnosis discovers maintenance patterns and system failures, uses operator knowledge for pattern comparison, and simultaneously provides ML control to perform RCA of a failure. Popular RCA methods are case-based reasoning and big-data search, both resulting in getting a fault diagnosis.
4. *Fault prognosis unit:* this unit produces a prognosis and decides on action items which may include the following: (1) automatic intervention, (2) operator intervention using decision-making, and (3) no intervention. In all cases, the logic behind a failure mechanism is compared and matched with a pre-defined problem-solving action plan. Contextualizing failure data in AR gives the operator real-time support.

5. *AR interaction unit:* all interactions between the database architecture, the AR technology, and the operator interaction are incorporated in this unit. Here, interoperability and real-time data processing are input for AR instructions to the operator. To communicate with the AR technology, the unit deploys a gateway to visualize the maintenance instructions in AR. The database architecture enables context-aware data access, allowing operators to retrieve relevant information based on their current location, task, and environmental conditions.

To discover maintenance patterns, fault specifications, and rules, the failure needs to be classified based on the failure type and specification. Classification of the failure can be performed in different ways varying from ML models such as support vector machine (SVM), Naïve Bayes (NB), and logistic regression (LR). SVM serves as a widely-used ML method in health state recognition and is a supervised learning method which is widely concerned with classification tasks. An application of SVM for high-speed rolling stock combines a data-driven approach, fault detection, and an implemented built-in monitoring system by using an imbalanced dataset [147]. The NB classifier is based on the common assumption that all features are independent of each other given the category variable [148]. Despite the simplifications the method uses, the NB classifier is often used as a baseline in text classification because of its fast implementation and it works quite well in many complex real-world applications. With appropriate pre-processing, NB is highly competitive with more advanced methods such as SVM. LR provides high accuracy of analysis because of its capability of computing the probability value rather than calculating a score [149]. In previous research, LR is used for tackling text categorization problems and shows the same performance as that of SVM. Before ML algorithms are implemented on a specific dataset, pre-processing text data is highly important to filter the data, including term frequency-inverse document frequency (TF-IDF) vectorization features.

AR plays an important role in different units: data acquisition, fault prognosis, and AR interaction. Academic research is focused on the development of structures to perform data capturing [150]. Tracking techniques and using sensor data and AR guidance are gaining more popularity among academics and industry. The fault diagnosing system requires spatial mapping via AR to provide the operator with troubleshooting information. The online and offline generated information is collected and combined with AR to construct a real-world troubleshooting scenario.

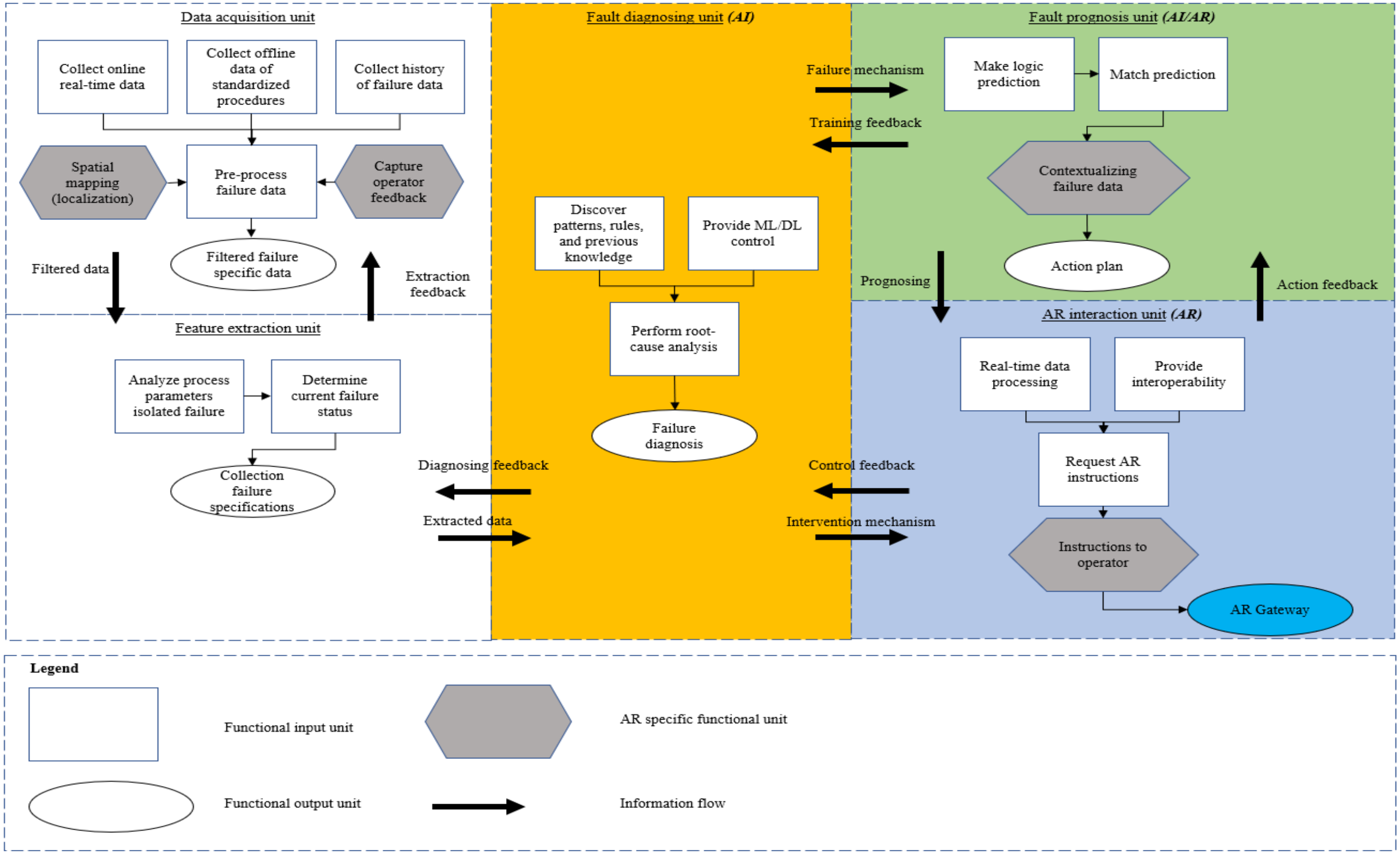


Figure 6.4. AR database architecture.

6.5 Case study

This section describes an implementation of the AR database architecture, deployed in a real-life case study in an industrial setting. The case study was performed in NS. The purpose of this section is to serve as a proof of concept and to validate the suggested AR database architecture. The case study demonstrates the feasibility of the proposed architecture and shows its real-world potential and effectiveness. In addition, it represents a unique endeavour to ensure data is centralized, prioritized, structured, and available for the operator at all times.

6.5.1. Case study perspectives

More interaction between the field of IT and organizational science is essential for implementing technological change in the institutional contexts that reshape economic and organizational activities [151]. Understanding and guiding techno-social developments requires knowledge of technological systems, social processes, and interactions. The case study is therefore focused on three different perspectives: (1) the scientific perspective, (2) the organizational perspective, and (3) the technological perspective. The scientific perspective focuses on testing the AR database architecture, i.e., the interaction and interrelations between the major units. The goal of this perspective is to identify the underlying links and interrelationships among the key units. The organizational perspective focuses on the future AR troubleshooting methods, i.e., the required data infrastructure and data backbone. Troubleshooting IT/OT rolling stock failures is time-consuming and has a high impact on maintenance operations, overall rolling stock availability, and thereby maintenance costs. The technological perspective focuses on the interconnection and readiness of available technologies, i.e., the application and combination of ML methods and AR technologies. Furthermore, the use of a case study provides practical verification of the proposed architecture.

6.5.2. Sanitary failure

Previous research was conducted to support maintenance operators using AR decision-making [152]. Fault diagnosis requires data input from multiple sources of information, all of which have different structures, formats, and content. With an AR database architecture, data can be collected from various sources. In this study, the focus is on the VIRM-m1, a refurbished double-decker rolling stock series that can present IT/OT system failures [107]. The interview session revealed that operators desire direct access to information through an AR tool that automatically documents and stores all relevant information and presents real-time data on failed IT/OT systems. Current maintenance procedures consist of consulting various sources of information, leaving the operator without up-to-date and complete information for troubleshooting. Based on a statistical analysis of operational rolling stock data performed by maintenance engineers of the company, the CAN system fails often and is identified as a complex IT/OT system. The CAN system is deployed for data transmission in multiple rolling stock subsystems such as the sanitary system, the climate system, the security system, the lights, and the low-voltage system.

Real-time operational data from 87 trainsets show that the sanitary system failed 1461 times in three months. Failures in this subsystem have a high impact on rolling stock operations, as the rolling stock must be taken out of service. Figure 6.5 presents the identified sanitary system of the rolling stock with its main components: the vacuum toilet and the bioreactor. The vacuum toilet consists of (1) a toilet bowl with a water-level sensor, (2) a water flushing system, (3) an intermediate tank, (4) a pinch valve, (5) a valve block, and (6) a control and signalling system. The vacuum toilet components are controlled by the toilet PLC and ensure that after operating the flush button, the contents in the toilet are transported to the bioreactor. A bioreactor is a composite unit that biodegrades solids and sewage from the vacuum toilet and the sink. The bioreactor provides (1) separation of solids and water, (2) filtration and neutralization of sewage by a bacterial colony, and (3) neutralization of residual water by heating and discharging this on the railroad.

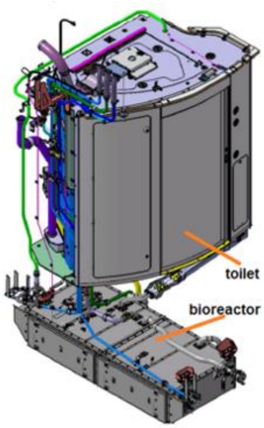


Figure 6.5. Sanitary system: toilet and bioreactor [153].

When rolling stock enters the maintenance facility, the operators conduct tests and trials to assess whether the IT/OT failure is justified. After this, the operator makes a fault diagnosis and performs a maintenance action accordingly. Therefore, this study focuses on the following maintenance procedures: ‘test and analysis’, ‘diagnosis’, and ‘maintenance’.

6.6 Results

The relevant content of the case study results is introduced in detail, including the dataset, the experimental setting; the data handling procedure and the pattern discovery. The data handling procedure involves the collection and storing of data, while the data processing cleans, analyses, and classifies the data. This is followed by discovering maintenance patterns that structure the fault diagnosis information.

6.6.1. *Data handling procedure*

The first stage of data processing focuses on data collection. Focus is put on obtaining reliable system failure data. To ensure the quality and reliability of the data, data sources must be reliable and well-built [154], and data must be accurate, complete, and relevant to the system failure. A database is created in MySQL to create, modify, and extract data from the relational database. The data comes directly from collected maintenance information from the company. Pre-processing company data involves cleaning and checking for duplicate, incomplete, and irrelevant data and is performed using Python 3.8 (Spyder 4.1.5).

While processing is typically the first stage, data analysis is largely considered the next stage of the overall data-handling process. Data analysis shows what maintenance patterns and insights can be found from the representative company data. Sequential pattern mining is a topic of data mining that deals with discovering patterns from a sequence of activities. Sequential pattern mining is an important data mining problem with broad applications, varying from customer purchase behaviour, Web access patterns, and disease treatments [155], and is, therefore, suitable for maintenance pattern mining. For this analysis PrefixSpan algorithm is used to mine frequent sequential patterns, due to its ability to grow longer patterns from longer ones and the pattern growth is more elegant than frequent pattern-guided projection [155]. The PrefixSpan algorithm first scans the database to find the frequent 1-sequence patterns. Then the projected database determines the prefix for each of these sequential patterns. From the prefix-projected database, the algorithm evaluates all the length 2-sequential patterns having the same initial prefix. It then determines the prefix projected database for these length 2-sequential patterns. The same steps are repeated recursively till no more sequential patterns can be found.

After the pattern mining procedure, the results become understandable to interpret and then visualized through AR to the operator.

6.6.2. *Data processing*

Figure 6.6 presents the data handling procedure of the case study. Maintenance data of all sanitary failures of the VIRM-m1 are collected from 2017 to 2022 [107], resulting in data entry of 3050 instances. Data is processed both manually and by utilizing NLP for analysis. Initially, the data is manually analysed to eliminate uncertainties. NLP can understand text and spoken words automatically and offers great automation possibilities [146]. Current NLP methods and algorithms predominantly focus on several high-resource languages such as English, Chinese, and French [145]. Because the text data is Dutch, translating Dutch text into English is unavoidable. Both methods are used, compared, and combined to represent the processed company data.

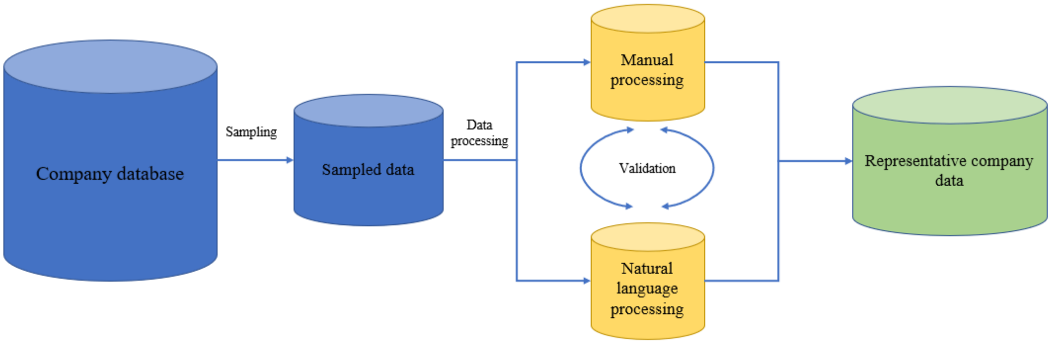


Figure 6.6. Data handling procedure.

Manual pre-processing data (MPD) is primarily intended to filter, sort, and pre-analyse data. In this way, inaccuracies are filtered that are normally not extracted. However, MPD is prone to the risk of human failure. The following procedures are used for the MPD:

- Removing duplicates
- Eliminating non-informational text inputs
- Categorizing and classifying text inputs

The goal of using NLP is to automize the process of understanding unstructured maintenance text data and retrieve meaningful information. The following procedures are used for the NLP:

- Translating Dutch to English
- Removing duplicates
- Eliminating non-informational text input
- Removing stop words
- Word tokenization and stemming
- Word lemmatization

After pre-processing and combining MPD and NLP methods, the data is labelled in different categories (Table 6.3) and 650 data instances are left.

Table 6.3. Labels of the maintenance procedures.

Label 'Test and Analysis'	**Label 'Diagnosis'**	**Label 'Maintenance'**
Occurs often	Check	Perform check
First report	Defect thermostat	Clean sensors
	Door PLC	Combination: flush, reset, test
	Error disappeared	Failure disappeared
	Error solved	Function test
	Grey water tank full	Further investigation required
	Hygienic unit broken	Another sub-system failure

Label ‘Test and Analysis’	Label ‘Diagnosis’	Label ‘Maintenance’
	Multiple errors present	Physical system maintenance
	No water	Refill water
	Frost discharge	Service flush
	Toilet full	Soft reset
	Only error information is available	Software
	Physical system error	Unblock toilet
	Pipe temperature error	
	Sensor dirty	
	Service flush	
	Software	
	Tank dirty	
	Tank leakage	
	Software error	

Hereafter, the data is split into training and testing data sets. The training data set will be used to fit the model and predictions are performed on the test data set. Empirical studies show that the best results are obtained when the training data constitute 80% of the data input and the test data constitute the remaining 20% of the data input [156]. The TD-IDF method is used to convert text data into numerical feature vectors because of its capability to determine what words are frequently used throughout the dataset. To predict the outcome of the classification accuracy of the ‘test and analysis’, ‘diagnosis’, and ‘maintenance’ phases, SVM, LR, and NB classifier algorithms are used. All accuracy results are approximated and are presented in Table 6.4.

Table 6.4. Accuracy of a classification method for different maintenance phases.

Rolling stock maintenance phase	Classification method	Accuracy (%)
Test and analysis	LR	~79
	NB	~75
	SVM	~83
Diagnosis	LR	~70
	NB	~65
	SVM	~68
Maintenance	LR	~61
	NB	~52
	SVM	~59

For this study, the accuracy can only be approximated due to the limited input data. From Table 6.4, it is concluded that the approximate accuracy of the method is different for each maintenance phase. Test and analysis text data are short and to the point, whereas maintenance text data is wordy and often unclear. For example, one entry of the maintenance text data is: *“pulled the pantyhose out of the bowl and used several service flushes to empty the rest of the bowl, the toilet works fine again”.*

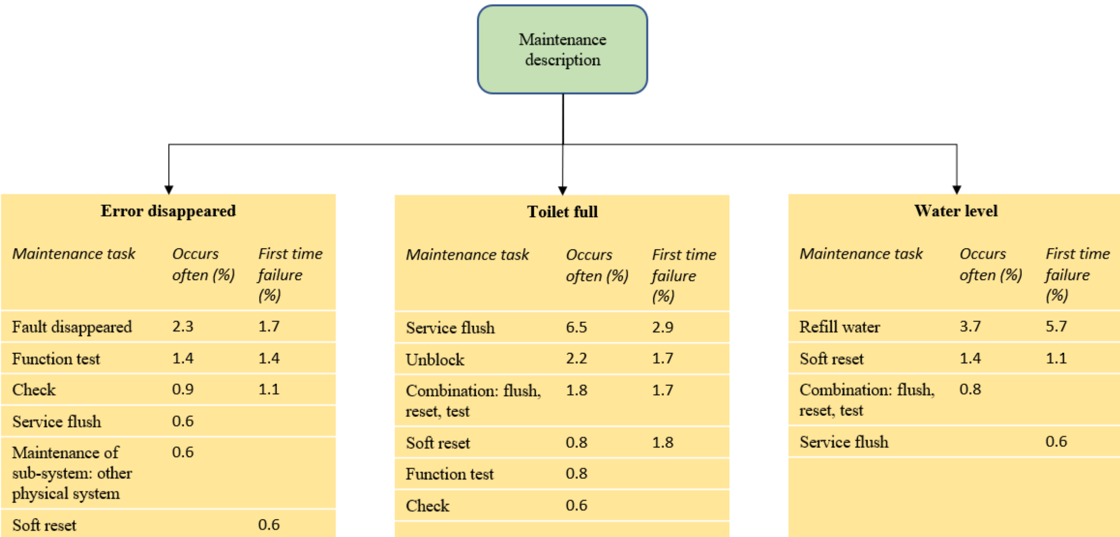
The NLP should classify the maintenance text input as “unblock toilet” and “service flush”, however now it is only classified as using a service flush to solve the failure.

6.6.3. Pattern discovery

After determining the approximate accuracy of the representative company data, it is possible to discover maintenance operations patterns of the rolling stock. PrefixSpan is used to discover the most occurring patterns; the frequent sequential patterns from the initial set of data. As a result, 159 sequential patterns with a frequency of 4 are selected. The sequential length of the patterns is 3 due to the limited maintenance strategies available from the ‘maintenance phase’. The results are presented in Table 6.5 and show the corresponding maintenance action related to the failure description. Column 2 is focused on maintenance descriptions that occur more often whereas column 3 focuses on maintenance descriptions that have not been reported before.

6.6.4. Pattern mining analysis

The failure causing the diagnosis ‘toilet full’, caused by a clogged toilet, is the pattern that occurs most frequently (Figure 6.7). This is followed by the failure causing the diagnosis of ‘water level’, caused by the water level in the toilet system not being sufficient. This is followed by the failure causing the diagnosis of ‘error disappeared’.



Error disappeared

Maintenance task	*Occurs often (%)*	*First time failure (%)*
Fault disappeared	2.3	1.7
Function test	1.4	1.4
Check	0.9	1.1
Service flush	0.6	
Maintenance of sub-system: other physical system	0.6	
Soft reset		0.6

Toilet full

Maintenance task	*Occurs often (%)*	*First time failure (%)*
Service flush	6.5	2.9
Unblock	2.2	1.7
Combination: flush, reset, test	1.8	1.7
Soft reset	0.8	1.8
Function test	0.8	
Check	0.6	

Water level

Maintenance task	*Occurs often (%)*	*First time failure (%)*
Refill water	3.7	5.7
Soft reset	1.4	1.1
Combination: flush, reset, test	0.8	
Service flush		0.6

Figure 6.7. Maintenance pattern mining results – most occurring failures.

Table 6.5. Pattern discovery – failure connected to maintenance action.

Failure description	**Maintenance description – occurs often (occurrence rate)**	**Maintenance description – first-time failure (occurrence rate)**
Other: physical system error	• Maintenance of sub-system: another physical system (3.2%)	• Maintenance of sub-system: other physical systems (2.8%) • Soft reset (1.7%) • Function test (0.8%) • Check (0.6%)
Error disappeared	• Fault disappeared (2.3%) • Function test (1.4%) • Check (0.9%) • Service flush (0.6%) • Maintenance of sub-system: other physical systems (0.6%)	• Function test (1.7%) • Fault disappeared (1.4%) • Check (1.1%) • Soft reset (0.6%)
Software	• Software update (0.8%) • Soft reset (0.6%)	• Not applicable
Toilet full	• Service flush (6.5%) • Unblock (2.2%) • Combination: flush, reset, test (1.8%) • Soft reset (0.8%) • Function test (0.8%) • Check (0.6%)	• Service flush (2.9%) • Soft reset (1.8%) • Combination: flush, reset, test (1.7%) • Unblock (1.7%)
Sensor dirty	• Cleaning sensors (2.9%) • Soft reset (0.6%)	• Cleaning sensors (2.5%)
Hygienic unit broken	• Maintenance of sub-system: other physical systems (1.8%) • Soft reset (0.6%)	• Maintenance of sub-system: other physical systems (0.8%)
Frost pipe temperature	• Soft reset (0.6%)	• Soft reset (0.8%)
Multiple errors	• Soft reset (0.9%)	• Not applicable
Toilet PLC	• Soft reset (1.1%)	• Not applicable
Water level	• Refill water (3.7%) • Soft reset (1.4%) • Combination: flush reset, test (0.8%)	• Refill water (5,7%) • Soft reset (1.1%) • Service flush (0.6%)

Most occurring maintenance descriptions (Figure 6.8) are caused by the failure causing the diagnosis of ‘toilet full’ and ‘error disappeared’, resulting in a maintenance action of performing a service flush (7.1%). Other often occurring maintenance tasks are performing a soft reset (6,6%), maintenance of a related physical system (5,6%), and refilling water (3,7%). However, when an error has not been reported before (First-time failure), most maintenance solutions are based on giving the toilet a soft reset (6%), followed by refilling water (5,7%), maintenance of a related physical system (3,6%), service flush (3,5%), a function test (2.5%) and cleaning sensors (2.5%).

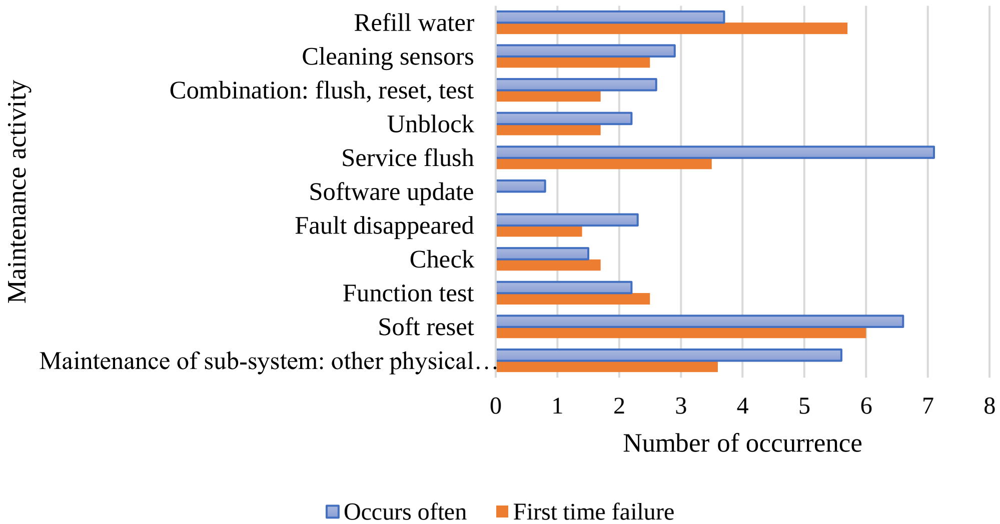


Figure 6.8. Maintenance pattern mining results – maintenance description.

6.7 Discussion

In section 6.6, the effect of all AR database architecture units is shown and deployed in the rolling stock maintenance procedure of a railway company to develop and reshape the system architecture. This section reflects on the three perspectives to understand and justify the importance of an AR database architecture. Also, application methods are discussed in detail.

6.7.1. Scientific perspective

Sequential pattern mining of unstructured data is difficult due to the existence of unclassified and fuzzy data, to overcome this, other work use the concept of key words dictionary to extract events in text [154][157]. If keywords from the pre-set dictionary are in the text, the content described in the text is classified as the key concept. However, it is difficult to ensure the content of text descriptions only by matching. In addition, building a key concept dictionary is time-consuming and subjective since experts in the field need to identify key concepts and determine keywords.

An example of using PrefixSpan to explore frequent sequential patterns from a precedence enterprise sequenced database for technology opportunity discovery is explored by Choi et al [158]. Precedence enterprise technological sequence can provide various results by adjusting the Prefix according to the philosophy or purpose of the target firm. However, this affects the sequence of actions and thus the accuracy of the method.

6.7.2. Organizational perspective

The case study emphasizes the importance of collecting reliable and complete data in the data acquisition unit. It was illustrated that text data requires intensive and accurate data handling procedures to be used in the feature extraction unit. The current combination of MPD and NLP ensures accurate data clustering for the ‘test and analysis’ phase. For the ‘maintenance’ phase more in-depth language processing is required, consisting of short, clear, and to-the-point text input. Initially, text data was processed in Dutch which led to even worse classification accuracy. The operator’s input is of great importance since he gives the text input at the various rolling stock maintenance phases.

The proposed pattern mining in the case study is based on a combination of manual and automatic processing of text data. To solve the problem of unstructured text data, the similarity labelling method is used to classify events based on word embedding. Combining manual and automatic text processing procedures ensures objective and efficient feature extraction. The methods proposed in this chapter can be applied in many fields as long as the text data is clear and structured.

Sequential pattern mining can discover the relationships between making a fault diagnosis and providing the maintenance solution. This will effectively change the passive maintenance strategy of organizations and update the maintenance support mode. To discover patterns of the maintenance operations, the PrefixSpan algorithm was used. Only sequential patterns with a length of 3 are considered valid sequential patterns. This cut-off value was set due to the restricted maintenance information available. Distinguish in pattern mining was made based on the number of occurrences to analyse the maintenance strategy for errors that have not been documented in the system. If a failure has not been documented before, most maintenance solutions are to perform a soft reset. Performing a soft reset does not address the root cause of the problem and thus this maintenance action will not solve the failure. Correct classification and labelling of the distinguished railway maintenance operations will ensure clear and structured pattern mining results.

Organizations, supported by researchers, should create roadmaps to embrace the transformation to smart maintenance before introducing new technologies and, thereby, new data infrastructures.

6.7.3. Technological perspective

Data reference architectures are not yet available in detail for new technologies and therefore implementation of such remains difficult [159]. There is a need for a database architecture compatible with CPS, ML approaches, RCA, and case-based reasoning for AR technology implementation and adoption [159]. Therefore, this work combines technologies that make troubleshooting complex maintenance failures as independent as possible and, at the same time, as linkable as possible. AI and AR are both individually likely to help advance troubleshooting complex failures and give the operator relevant IT/OT failure information. The combination and integration of both have the potential to support this even further. AI, in particular ML, is used to extract analyse, filter, and structure the desired information. Based on the discovered maintenance patterns using the AR database architecture, a new maintenance strategy can be developed and an appropriate action plan can be formulated using an AR technology that deploys a gateway.

6.7.4. Limitations

The AR database architecture illustrates limitations in the context from a socio-technical point of view.

Database architecture. There is a need to change the mindset regarding reference architectures to address the general architectures. Technologies, ML approaches, and CPS should be combined to make machines and systems as independent as possible while being connectable at runtime to achieve a balance between independence and connectivity between components.

Organizational compatibility. Future work in operationalizing the AR database architecture may involve further refinement of infrastructure, software components, and continuous improvement of operational processes based on user feedback and evolving industry requirements. Implementation of AR concepts by organizations remains a challenge, especially in defining how the information and communication flows that crosscut AR systems. The compatibility and integration between standards of different industrial domains require deeper investigation.

Operator input. The AR database architecture depends on operator input; ideally, the architecture should be based on automated data input. Currently, operator input is required for FTA, FMEA, and decision-making procedures to analyse the nature and root cause of a failure. Documenting maintenance operations is a source of information needed for the AR database architecture.

Data availability. The case study has limited data input and therefore it is difficult to conclude the scalability and adaptability of the architecture. To continue the performance of the AR database architecture, organizations must ensure that all maintenance-related data becomes available.

Data processing limitations. A limiting factor for performing data processing is the requirements coming from NLP. The data requires intensive processing and analysis before discovering the maintenance patterns. In addition, the translation of Dutch text to English documents is contentious.

Technology. AR technology provides the ability to visualize structured maintenance information to the operator. However, before AR can be utilized, IT/OT data must be collected, structured, filtered, and analysed. In addition, online data must be synchronized with real-time rolling stock conditions.

6.8 Conclusion

At present, there is a need to have a database architecture able to gather and collect data, extract features to perform troubleshooting and have an AR gateway to support operators in contemporary maintenance environments. This AR database architecture pre-processes text data for further use in data mining efforts to discover maintenance patterns and thereby develop a rough analysis of generic maintenance records. The AR database architecture has five units enabling the application of AR: (1) data acquisition unit – collecting real-time online and offline data requiring pre-processing, (2) feature extraction unit – isolating failure parameters and identifying failure status, (3) fault diagnosis unit – discovering maintenance patterns and rules by using operator input to identify the root cause of the failure, (4) fault prognosis unit – prognosis and determining action plan to solve the failure, and (5) AR interaction unit – interacting between the database and the AR technology.

A case study was performed at a Dutch railway company to demonstrate the feasibility of the proposed architecture and show its real-world potential and effectiveness. The case study showed that pattern handling, data processing, and pattern discovery are the backbone of the AR database architecture. It was found that data should be centralized, prioritized, structured and available to the operator at all times.

Sequential pattern mining is an appropriate way to excavate text data, however, when the text data is unstructured, traditional pattern mining methods are no longer applicable. Therefore, this chapter proposes a combined method in which manual processing methods are combined with NLP methods.

The proposed architecture provides the operator with structured maintenance information on IT/OT complex failures. The AR database architecture serves as an invaluable reference for those wishing to implement smart technology control in organizations. Future research includes comparing the AR database architecture with future proposed architectures and validating it by implementing it in other case studies that adopt either the architecture or parts of it.

Chapter 7 – Using functional blocks for rolling stock troubleshooting: Sequential Augmented Reality Assist (SARA)

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7.1 Theme IV: Functionality of AR troubleshooting

Maintenance and troubleshooting contribute to the overall economic efficiency of rolling stock throughout its lifecycle, yet these activities are resource-intensive and incur significant costs. In the era of Industry 4.0 implementation, the escalating complexity of rolling stock poses challenges in troubleshooting and maintenance decision-making. Recognizing this, there is a pressing need for a structured solution that empowers maintenance operators with tools for effective organization, analysis, and real-time presentation of rolling stock system failures, facilitating streamlined troubleshooting and maintenance guidance. This chapter's significance lies in addressing the critical challenges of troubleshooting and maintenance decision-making in the context of rolling stock systems (Figure 7.1).

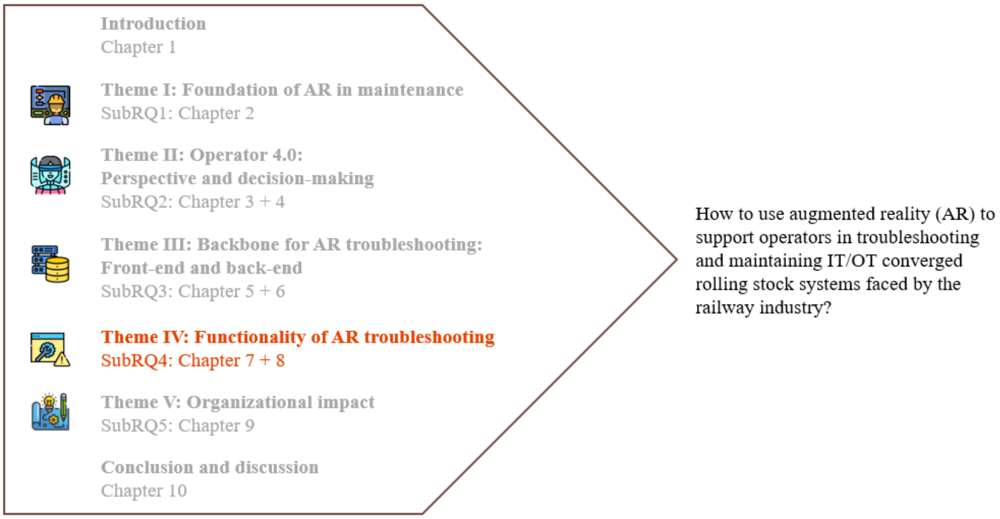

Figure 7.1. Theme III: Backbone for AR troubleshooting: Front-end and back-end.

Functional blocks, providing systematic structuring of processes, and AR, offering enhanced visualization and decision support, emerge as solutions to navigate and streamline these challenges in the evolving industrial landscape. The intricacies of existing fault-diagnosing systems, particularly interconnected transmission of functional blocks for troubleshooting and AR integration, lack detailed explanation, hindering effective solutions. To address these challenges, this work leverages AR for troubleshooting rolling stock failures, introducing functional blocks to (1) collect maintenance and fault data, (2) integrate maintenance information based on failure diagnostics and maintenance patterns, and (3) deliver this information to maintenance operators through AR. The developed SARA prototype, developed in this study, exemplifies the sequential implementation of AR troubleshooting functional blocks in an industrial context, providing a systematic solution to the complexities involved.

7.2 Introduction

Swift advancements in technology, data, and analytics have propelled maintenance operations beyond a mere reactive process, leading to a proliferation of digital solutions [25]. Digital maintenance incorporates traditional maintenance functionalities with newer digital tools and methods to serve the maintenance purpose best. Major functionalities of digital maintenance are monitoring, predicting, diagnosing, troubleshooting, optimizing, reporting, commissioning, modernizing and supporting maintenance actions [160]. Technological advancements are one of the key components responsible for the evolution of maintenance [160]. The rolling stock industry highlights the need for dynamic real-time information exchange between IT and OT systems [161]. In addition, troubleshooting rolling stock failures has become more data-driven, and a large amount of intertwined maintenance and failure data increases the need for a comprehensive system that presents the data in an interpretable and understandable manner. AR is an important tool for the digitization services taking place in industrial maintenance work environments. Active research for training and guidance of maintenance operators utilizing AR is growing [162]. Data sharing, transferring, analysing, and processing require visualization and contextualisation support [163], AR can display a wide variety of data in a perceivable way, easily controllable, and interactable by maintenance operators.

A literature review presented the most common components and their interactions of an AR system: (1) UI allowing two-way communication between the technology end-tool and the user, (2) tracking system for placing digital objects correctly and aligning in the physical worlds, (3) sensor system to obtain information from the environment, (4) visualisation technology for presenting the digital content in the real environment, (5) processing unit responsible for executing software in AR, and (6) an external database for data storage and management [164]. The literature study reveals that future work is required towards real-life applications having adaptable content. Data processing, storage, management, and exchange needs to be flexible to be adapted to different needs. In addition, future research is required on how AR solutions can be integrated into data analysis. This can be tackled by integrating real-time data from maintenance information systems.

In demanding work environments, maintenance operators play a crucial role and require information and expertise to perform maintenance tasks, ranging from servicing rolling stock to the processes of replacing and testing components. Rapid technological, data, and analytic advantages have facilitated the evolution of maintenance operators, shifting to a maintenance domain encompassing AR solutions. AR enables operators to access the digital world through a layer of real-time information positioned on top of the physical work and contributes to the human-centric industrial environment [165]. Gattullo et al. align AR methods for authoring new manuals with six principles from Industry 4.0 concepts: interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity [166]. The research proves general guidelines for technical manuals in AR. However, there is no centralization, interoperability, and organization of documentation for embedded machine, operator, and maintenance support. Yew et al. (2009) utilized AR interfaces as an intuitive way to interact with Cyber-Physical Production Systems (CPPS) [167]. The focus is on creating an easy-to-interact AR tool, allowing resource discovery, searching, and matching algorithms to categorize resources on the grid for users with different needs. Future work is required on creating object interaction that has a unique interface fitting its required functionality. Studies reveal that human-AR collaboration benefits from proactive prototyping and adaptive techniques [165].

AR-based troubleshooting is a complex process requiring translation of the basic characteristics and properties into a logic model, such as an existing event tree, starting from a description of the AR-based troubleshooting deriving all information and actions needed concerning the intended function of the process. The concept of functional diagrams provides such description by proposing building blocks representing a function that a particular collection of engineering systems and human actions is supposed to perform [168] and is used in the field of troubleshooting and Industry 4.0 concepts [169][170]. An important feature of the functional blocks is that they can simplify complex AR-based troubleshooting by giving a natural hierarchical decomposition by combining inputs and states of systems to provide outputs straightforwardly supporting the analysis of engineering systems.

AR-based troubleshooting combines ML, CPS, AR, standardized maintenance procedures for fault diagnosing, and 3D visualization of maintenance activities, and guides operators in decision-making for the maintenance work (Figure 7.2) [130][171]. The application of AI methods brings process automation and process optimization caused by feature classification, sensor data prediction, processing of large datasets, and signal analysis [172]. Advances in 5G and IoT technology combined with various sensors make real-time collection and transmission of sensor information to a cloud server possible [172]. Many studies, varying from manufacturing to medical practices, have focused on creating synergy between the virtual and physical worlds [128][173]. The current troubleshooting methods focus solely on identifying and analysing specific faults or malfunctions, following standardized maintenance procedures, and systematically addressing and resolving system failures. In contrast, the AR-based troubleshooting concept in this work brings synergy between the virtual and physical worlds by representing sensor data, maintenance information, and analytics with virtual and physical objects through AR. This approach enhances the troubleshooting of rolling stock system failures in a virtual environment, surpassing the limitations of traditional methods and fostering a more comprehensive and efficient maintenance workflow.

This research incorporates four perspectives related to AR-based troubleshooting for the railway sector (Figure 7.2): (1) rolling stock maintenance operations, for identifying and solving complex rolling stock failures, (2) AR-human interaction, to visualise and present step-by-step maintenance solutions, (3) connectivity, data, and computational power, to store and process online and offline data, and (4) analytics and intelligence, to process and make failure predictions.

Categorizing the connected fields helps to determine the impact and contribution of AR-based troubleshooting. This research adopts functional blocks and functional diagrams for effective and efficient analysis of the AR-based troubleshooting system, enabling hierarchical and systematic analysis, and enhancing and aligning rolling stock maintenance practices.

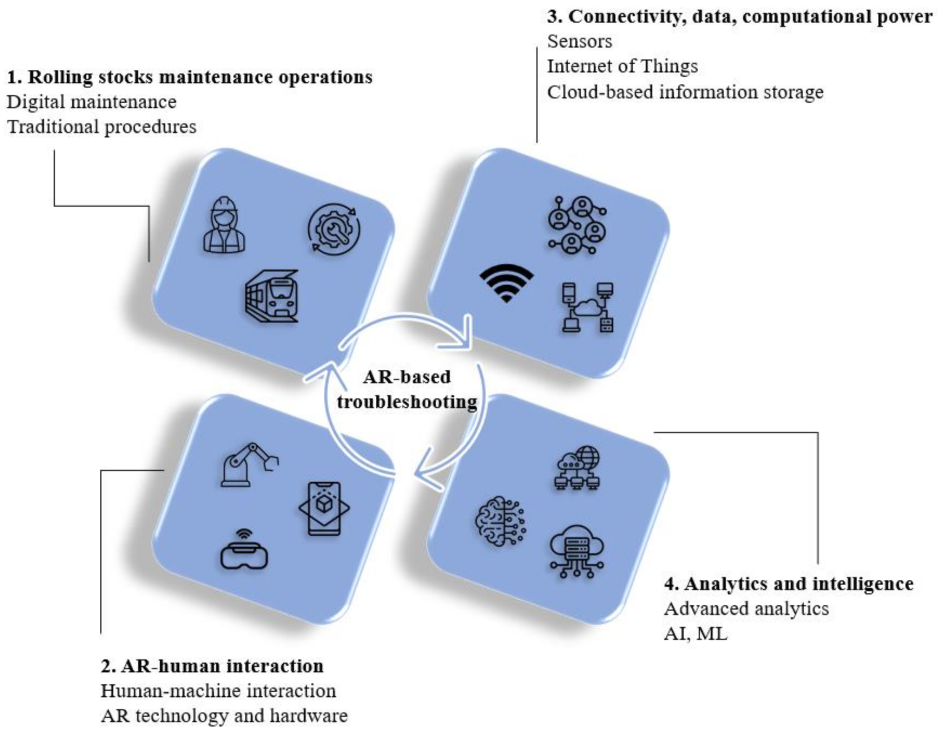

Figure 7.2. AR troubleshooting connection and application fields, adapted from [174].

The following research question is investigated in depth in this study: w*hat are AR-based functional blocks to develop troubleshooting tools?* This chapter presents a case study in the railway industry, NS as a rolling stock maintainer in practice. It aims to validate the functional blocks for AR-based troubleshooting operations. Railway companies witness a multitude of technology applications, e.g. AI, 3D printing, 5G, sensor techniques, Extended Reality (XR), and process mining, in and around rolling stock that has an impact on every partner in the railway sector [25].

The chapter is structured such that a preliminary analysis of the theoretical background of maintenance, AR-based troubleshooting functionalities and requirements, and challenges in designing AR troubleshooting prototypes is presented in section 7.3. Section 7.4 outlines the followed methodology, whereas section 7.5 describes the functional blocks of AR-based troubleshooting. Section 7.6 presents a detailed description of the railway company case by pinpointing the underlying research problem, identifying the objectives of the desired solutions, and describing the corresponding design and development part of the prototype design. Section 7.8 discusses the results and performance of the prototype solution. Section 7.9 outlines the discussion including the limitations and challenges of the study and finally in section 7.10 the conclusion of the conducted research and offers key recommendations for future research.

7.3 Context for AR-based troubleshooting

In the past decades, the maintenance industry has been under high development of empowering IT by data, predictive, and AR-driven models [175]. Data-driven maintenance methods use multi-sensor data fusion technology to collect necessary information, dynamically monitor the maintenance procedure, and support decision-making [175]. The development of AR-based troubleshooting functionalities is grounded in data-driven maintenance models, providing real-time monitoring and decision-support.

7.3.1. Rolling stock troubleshooting process

In recent years, preventive maintenance has become a preferred strategy for rolling stock maintenance. Using condition-based and predictive maintenance strategies is considered the preferred solution [176][177]. Although these strategies are well-known, the rail sector is struggling with their implementation. Previous work [171] reveals the process of troubleshooting rolling stock system failures in the Dutch rail sector (see Figure 7.3) and consists of (1) preliminary remote analysis, e.g. scheduling the maintenance work remotely, (2) analysis and testing, e.g. troubleshooting the maintenance failure on site, (3) diagnosis, e.g. diagnose the system failure based on troubleshooting results, (4) repair, e.g. performing the maintenance task corresponding to the system failure, and (5) validation, e.g. testing if the system failure is resolved. The functional building blocks proposed in this research contribute to the ‘Analysis and testing’, ‘Diagnosis’, ‘Repair’, and ‘Validation’ procedures on the maintenance site. The functionalities that these procedures should entail are discussed in the next section.

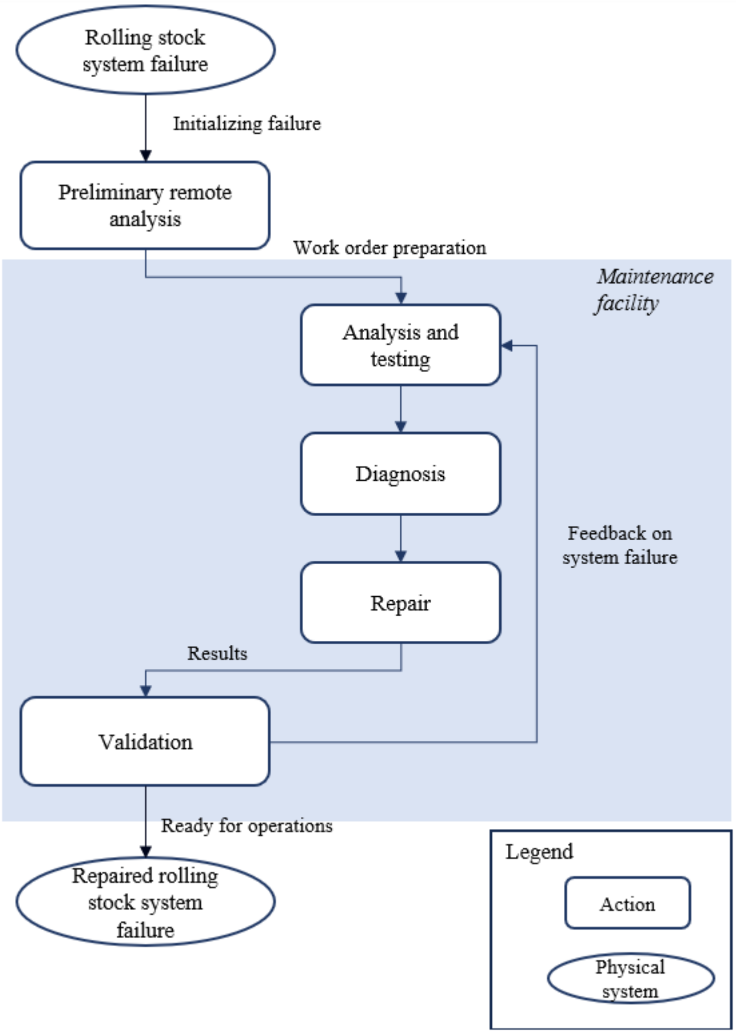

Figure 7.3. Troubleshooting process in the rail sector.

7.3.2. Basis for AR-based troubleshooting functional blocks

AR fault diagnosing has three main functionality requirements [130]: (1) fault detection and recognition in rolling stock and identification of potential effects of the failure that occurred, (2) countermeasures for a problem-solving strategy, e.g. KBS, consisting of existing maintenance procedures and fault analysis, and (3) visualizing and contextualizing the rolling stock failure through AR. Connecting these to the aforementioned troubleshooting procedures results in the pairing made in Table 7.1.

Table 7.1. Pairing troubleshooting procedure and AR-based troubleshooting functionalities.

Troubleshooting procedure	AR-based troubleshooting functionality
‘Analysis, test and diagnosis’	System referencing and fault-diagnosing
‘Repair’	Problem-solving
‘Validation’	Visualization and contextualisation

As mentioned in the literature, current fault diagnostic methods are divided into three categories: signal-based, mathematical modelling methods, and knowledge-based methods [169]. Signal-based fault diagnosing is widely applied in nonlinear systems but is unnecessary for establishing precision [178], whereas mathematical modelling methods use a precise mathematical model [179]. However, it is generally challenging to obtain engineering models and signal patterns that can reveal the potential effect of failures in a system combined with unpredictable human interactions [180]. Knowledge-based methods can improve the decision-making correctness and diagnostic process because of their self-reasoning capabilities and object information retrieval [180]. Typical knowledge-based fault diagnosing consists of a Knowledge Base (KB) and an inference engine to deduce new findings from the KB via reasoning methods that mimic the human thinking process [180]. AI algorithms can be integrated as a computational fault diagnosing unit, while AR facilitates real-time data streaming through visualization support. More research on combining AR spatial mapping with the processing power of AI while visualizing the results directly in AR is needed [130]. This integration has the potential to provide real-time spatial insights into complex systems, improving the visualization and understanding of data.

Topics such as digital maintenance, DT, and digital system reference contribute to proactive fault diagnosing by providing a holistic and real-time understanding of complex systems. The combination of AR, DT, and digital system reference fuses the virtual and physical worlds. DT and digital system reference include real-time simulation, diagnosis, prediction, and control whereas AR focuses on displaying information and facilitating interaction, while also providing feedback and maintenance tracking features [181]. As part of digital maintenance, rolling stock, maintenance procedures, and component data (both online and offline) are stored and readily available for analysis. Data-based diagnosing provides a new dimension to operators in finding the root cause of the problem and helps in making exact, prompt, and necessary decisions to fix the rolling stock or the sub-component [160]. AR-based troubleshooting allows operators to access the connected rolling stock to perform maintenance procedures by starting fault identification utilizing historical trends and analysis data [182]. DT enables real-time data transmission between the rolling stock and virtual spaces by digitizing the rolling stock and is capable of optimizing processes, predicting health status, and making decisions accordingly [183].

The industrial applications of DT have proved that DT can improve system stability, reduce maintenance time, and create economic benefits in the industry [184]. Several studies focused on the rapid construction of system decision-making models, such as fault diagnosis model construction of deep transfer learning [185] and overall remaining life prediction [186]. These methods make use of historical data to support the process of decision-making. More research is required on the applicability and adaptability of the method when the physical entity in DT changes [175].

The digital system reference reflects current, future, and potential production environments [128] and can be incorporated into rolling stock troubleshooting. The DT includes the collected online and offline maintenance and system failure data, the digital master is the envisaged and desired rolling stock health state, and the digital prototype is the predicted rolling stock system state based on simulations and operator experience. AR can be used as an interface between the operator and the digital interface by mapping real-time maintenance instructions in 3D. An AR interface requires input from rolling stock maintenance operations and system failure and should allow interventions during maintenance activities. The AR-based troubleshooting support aims to provide operators with the appropriate level of interaction, from the appropriate viewpoint and the appropriate filtering of information at the appropriate time. The digital system reference can be the backbone of this but operator input is required to determine what data or information carries valuable meaning. The usage of the digital system reference in combination with AR is essential, however, more applied research is key [128][187].

Maintenance tasks can be visualized and analysed according to the information gathered through fault diagnostics. Data captured and processed using AI and digital system reference support operators diagnosing rolling stock failures correctly by showing only appropriate maintenance information through AR. This can be done by (1) implementing sensors and data-capturing mechanisms on the rolling stock to collect relevant information about its performance, components, and conditions, (2) utilizing AI algorithms to process and capture data, (3) developing a digital system reference that accurately represents the rolling stock, including its components, systems, and interactions, (4) integrating AI and digital system reference, (5) implementing AI-diagnosis algorithms that leverage the digital system reference to accurately identify and diagnose potential failures, (6) utilize AR visualization to present customized maintenance information to operators.

AR is a powerful integrating, displaying, interacting, and computing technology. New AR authoring maintenance manuals for automatic failure diagnosis have to be within Industry 4.0 principles to offer real-time communication by using automated augmentation of visual aids [130]. The hardware-software choices of AR devices, e.g. HMD, HHD, projectors, and headphones, depend on the data capturing methods and clarity requested of existing information on the operation application, specific maintenance task, and operator [188]. The discovery of the actual needs, maintenance approaches, and development of human-AR-centric maintenance workflows are all urgent and worthy of further exploration [188].

7.4 Methodology

Design Science Research (DSR) is used to develop new technologies for solving socio-technical problems to effectively evaluate new and innovative solutions [189][190]. This method is chosen mainly for its general acceptance in human-in-the-loop computing that combines human and machine intelligence systems [191] and prior use in designing AR solutions [192]. To better align the research question with the presented methodology, an appropriate case within the railway industry was identified for further investigation. Additionally, the problem-centred approach of the DSR methodology was selected as the starting point of the conducted research. Figure 7.4 presents the proposed design process in this research. The processes involved are (1) problem identification and motivation, (2) setting objectives for a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication. Utilizing a case study in the railway industry, the research focuses on building an AR-based troubleshooting tool through prototyping. The goal is to demonstrate that functional blocks within the tool support a better understanding of AR-based troubleshooting, validating its effectiveness through evaluation and communicating the findings.

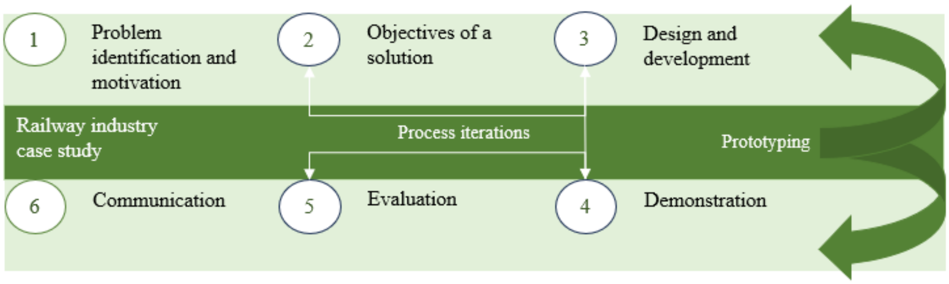

Figure 7.4. DSR method for AR troubleshooting, adapted from [189].

7.4.1. Data collection and acquisition

To gather a comprehensive overview of the experiences of participants who are expert operators, a mixed-method approach to collect data is utilized. The participants offer insights into the functionality of the proposed AR-based troubleshooting prototypes and contribute to the validation of the functional blocks. The study includes expert maintenance operators working at the Dutch railway company NS.

Qualitative data from operators is collected in 6 sessions through semi-structured interviews, workshops, and prototype testing, an overview of the number of participants, field of expertise, and topics for the session are presented in Table 7.2. Semi-structured interviews were held in session 1 to introduce AR, position AR in the organization, and explore potential case studies. This data aims to learn more about the potential use case and identify the limitations of this work. The goals of session 2, utilizing semi-structured interviews, are (1) to investigate how the operator is fed by the various information sources, (2) to explore what knowledge and information is missing, (3) to define what operator input is required, and (4) to define the opportunities to interact with a centralized data platform. Session 3 involves a workshop in which, in collaboration with operators, a specific train failure is examined and troubleshooting scenarios are explored. During sessions 4, 5, and 6 a prototype is tested for its troubleshooting capabilities and perceived usefulness. The decision to conduct three iterative prototype testing sessions for AR-based troubleshooting supports a user-centric, adaptive, and efficient development process, leading to a more robust tool. For these sessions, operator input is gathered using semi-structured interviews and observations.

Data collection took place at different maintenance facilities. The data collected from maintenance operators is analysed and processed utilizing ATLAS.ti [45]. The data is classified into various groups, each contingent on the functionality of the troubleshooting process. All results were verified for correctness and completeness with the operators.

Table 7.2. Data collection and session overview.

Session number	Data collection method	Field of expertise	Number of participants	Topic of interest	Session time (min)
1. Introduction interview	Introduction interview AR hardware introduction Data log	Maintenance, IT/OT	14	Positioning AR in organization, potential applications, preliminary case study selection	60
2. Functionality AR exploration interview	Functionality exploration interview Data log	Troubleshooting complex systems, teaching	4	Current information access and availability, data sources, required maintenance information, AR for troubleshooting, case study selection	45
3. Workshop	Workshop session Case study selection Data log	Sanitary systems, troubleshooting complex systems	6	Current troubleshooting strategy, required maintenance information, case study selection	90
4. SARA prototype testing (experimental mock-up)	Prototype testing Interview Data log	Sanitary systems	5	Information supply, accuracy, and accessibility, troubleshooting capabilities in experimental setting	90
5. SARA prototype testing (industrial setting)	Prototype testing Interview Data log	Troubleshooting complex systems	3	Information supply, accuracy, and accessibility, troubleshooting capabilities in industrial scenario	90

Session number	Data collection method	Field of expertise	Number of participants	Topic of interest	Session time (min)
6. SARA prototype testing (industrial setting)	Prototype testing Exit interview Data log	Sanitary systems, troubleshooting complex systems	3	Information supply, accuracy, and accessibility, troubleshooting capabilities in industrial scenario	90

7.5 SARA prototype development process

In earlier works, the importance of decision-making [152] and combining ML, AR, and maintenance policies is studied [130]. These insights served as the starting point of this work. The functional diagram for AR-based troubleshooting is not discussed, nor are the technical issues encountered and solved during previous studies carried out by the author or in the literature. To validate the functional diagram for AR-based troubleshooting a SARA prototype is developed. The SARA prototype is an AR-supported system that facilitates sequential maintenance information visualizations to operators. Fig 4 presents a holistic overview of the design and development process.

Hardware and software concepts explore and introduce AR systems to operators. Simultaneously, the troubleshooting scenario is discussed to set the functionality requirements of the prototype. The SARA prototype is iterated in steps II to IV of Figure 7.5 using operator input. Initially, a simplified sanitary failure is simulated and has to be solved by the operator through AR. Based on operator input, this prototype is further developed into a real-life simplified troubleshooting scenario (involving testing scenarios on the rolling stock to gain practical experience) and a real-life troubleshooting scenario (including all practical constraints and implications).

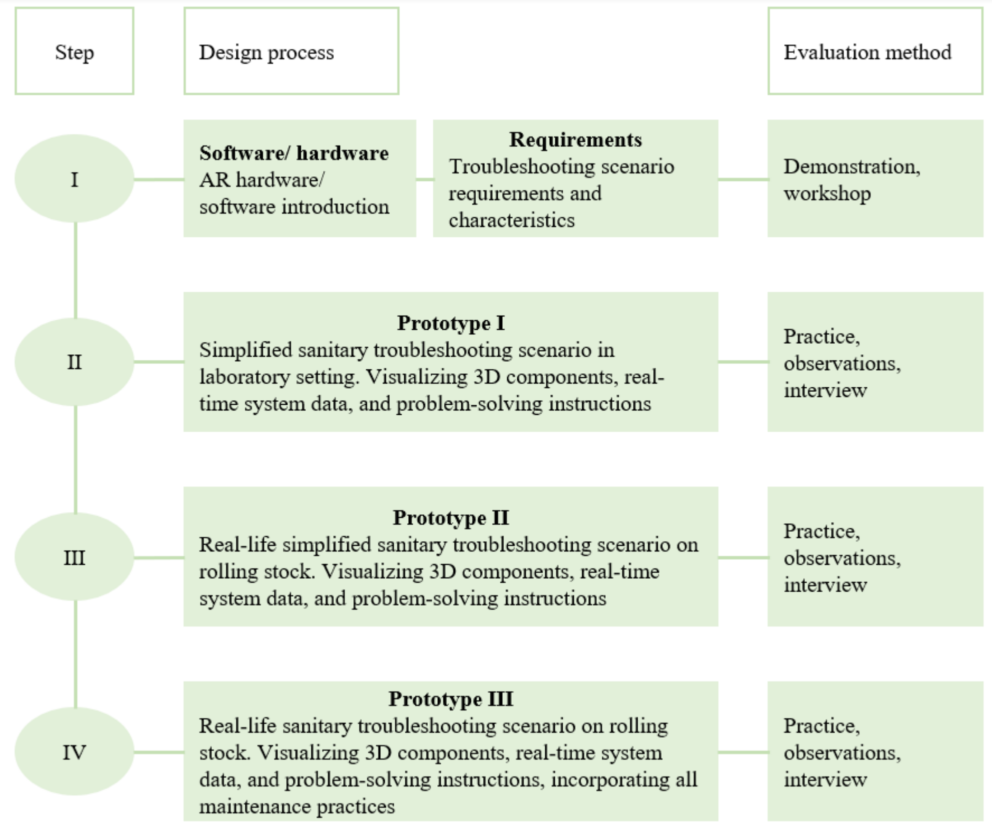

Figure 7.5. SARA prototype development.

7.6 Functional blocks of AR troubleshooting

Any typical troubleshooting procedure aims to comprehend, and identify the root cause of an issue, and rectify or repair failures in equipment. AR-based troubleshooting supports organizations to utilize AR technologies, ML, and maintenance data to improve traditional working methods. The AR-based troubleshooting functional block diagram comprises individual functional blocks, e.g. fault detection and recognition, providing problem-solving strategies, and visualizing and contextualizing the rolling stock system failure. The functional blocks are connected by the outputs of one of them constituting inputs to others. In the diagram, every functional block is associated with a specific partition of its outcome space. This partition is determined by the requirements of identifying whether a portion of the output serves as input to other functional blocks or represents an output of the entire functional block diagram.

Based on the continuous availability of real-time rolling stock data and backed by stored historical data, an AR-based troubleshooting functional block diagram is proposed, drawing upon the concepts from Section II(B) of this work. Upon arranging all functionality blocks in the AR-based troubleshooting functional block diagram, the requirements for effective troubleshooting assistance need to be delineated. These functional blocks are grouped into three overarching processes: (1) data collection and analysis, (2) information integration, and (3) information push. Each of these overarching processes comprises various blocks (see Figure 7.6) and are explained below.

- Data collection and analysis: online and offline maintenance data collection and analysis, including troubleshooting experience and historical maintenance procedures. Data collection, monitoring, and analysis are the basic and vital functions of AR-based troubleshooting rolling stock system failures [193]. Firstly, troubleshooting principles, system reliability design, and maintenance manuals are comprehensively analysed to obtain low-dimensional information, e.g. test information, diagnosis information, and maintenance information. Continuous availability of real-time rolling stock and maintenance data is a key concern as it aids in real-time (remote or on-site) monitoring of the rolling stock and its operating conditions. The assessment of the health state of the rolling stock and its components provides the basis for decision-making regarding the continued use or replacement. In addition, data collection and analysis contribute to diagnosing the system behaviour, maintenance pattern mining, and predicting future failures. The focus is on reducing rolling stock and component failures, increasing operability, and maintaining the equipment for consistent and longer use.

Maintenance and rolling stock data from various modules distributed across multiple locations can be collected and analysed together using cloud-based data fusion and data analytics [194]. By leveraging cloud-based data fusion, organizations can harness the benefits of a centralized, scalable, and accessible platform for analysing and deriving meaningful insights from maintenance and rolling stock data. The information about the rolling stock health can then be fed to the operators, creating a closed-loop troubleshooting process where the analysis informs and guides subsequent maintenance actions and collects feedback from operators.

- Information integration: information integration based on failure diagnostics and maintenance patterns, a dynamic prediction algorithm based on maintenance pattern mining techniques, and the general prediction model are used to establish a dynamic prediction model of information for troubleshooting [195]. Diagnosing faults and failures is a key functionality in troubleshooting rolling stock, involving a systematic analysis of symptoms, data, and indicators of system failures, that helps understand the root cause of the problem and provides the basis for solving them [160][196].

AR-based troubleshooting allows the operator to access the connected equipment perform operations remotely and troubleshoot the diagnosed failures. AR-based troubleshooting facilitates support promptly and starts the fault identification utilizing the historical trends and analysis data. The swift fault identification facilitated the prompt start of resolution. Recommendations and maintenance instructions can be given to the operator to fix the issue.

- Information push: an information push method based on integrated information flow for maintenance and troubleshooting. Operators are provided with contextualized and visualized AR maintenance guidance. Besides this, the maintenance operators provide the automatically received troubleshooting information to the dynamic prediction model so that the model can be continuously updated and optimized. The first function of the information push application is the visualization of maintenance procedures by configuring 3D visualizations of failed train components and maintenance activities. The operator can inspect the current health state of the rolling stock and request procedural details by exploiting real-time data. The second function enables user interaction with the 3D AR projection. The functionality of this interaction should facilitate a dynamic and intuitive user experience, allowing users to manipulate, explore, and interpret the AR content effectively. The third function exports all updates that the operators make during the utilization of the application. In this way, information exchange is performed, giving both operators and managers the ability to collaboratively work in a cloud-based environment.

Once all functional blocks are positioned in the AR-based troubleshooting functional block diagram, the requirements to effectively assist troubleshooting have to be specified. In formulating functional block requirements, operators and technical experts should be involved to ensure that the customized support aligns with the demands of the troubleshooting process and the technological capabilities. Additionally, maintaining flexibility to adapt to changing user needs and emerging AR technology advancements is key to the success of the AR-based troubleshooting system. The AR-based troubleshooting should be capable of accessing, logging, and storing relevant maintenance data for analysis and future reference [152].

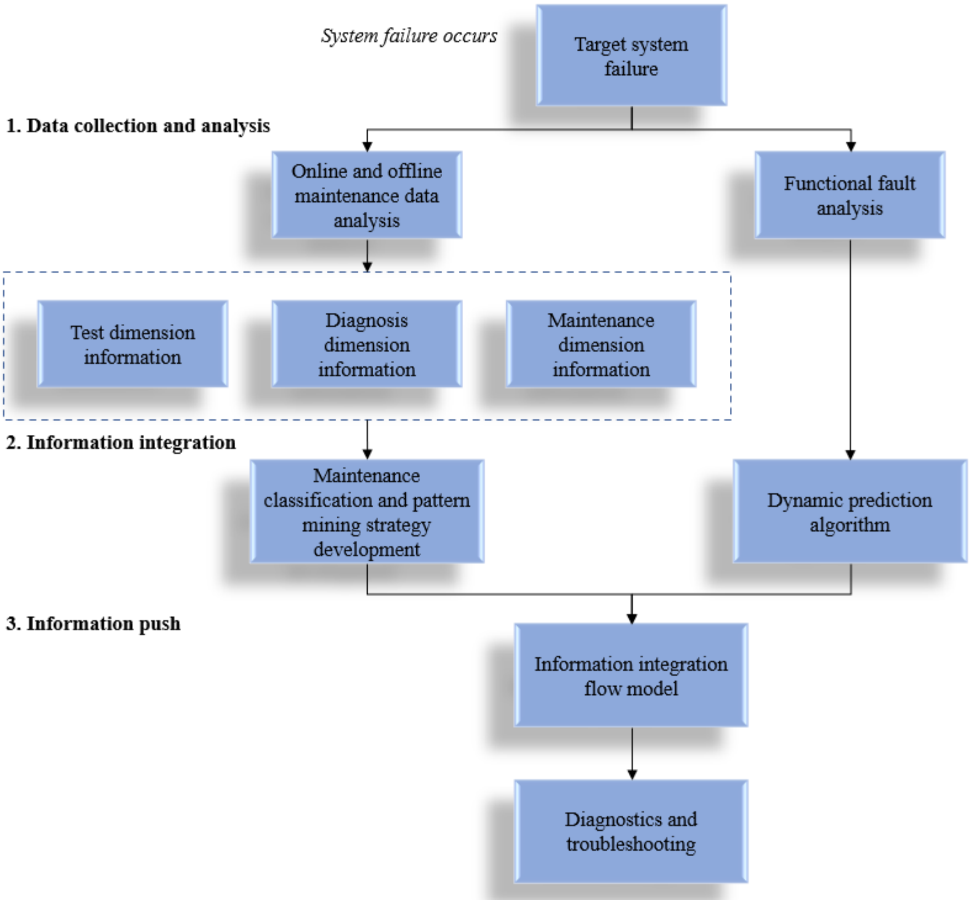

Figure 7.6. Functional block diagram AR-based troubleshooting.

Predictive algorithms can alert maintenance operators to impending failures, allowing for proactive repairs or maintenance actions. ML approaches can automate the analysis of maintenance data and enable quicker failure identification and response [197][30]. The digital information overlay must align with the physical object and object identification should be accurate and real-time. Users should be able to interact with the AR interface through gestures, voice commands, or other intuitive methods. The AR system should provide real-time feedback and operate with minimal latency.

The functional blocks in the AR-based troubleshooting system are closely aligned with specific functional requirements, creating a symbiotic relationship that enhances the overall capabilities of the system. The main functionality requirements for AR-based troubleshooting are listed in Table 7.3 so that the operator can utilize and change the system comfortably. An overview of how each functional requirement (Table 7.3) corresponds to the associated functional block (Figure 7.6) is listed next.

- Maintenance of procedural and rolling stock data;
  (A) Functional requirement: capture maintenance procedural and rolling stock data from existing operations within cloud-based environments.
  (B) Functional block: online and offline maintenance data analysis block.
- Interaction with online/offline information;
  (A) Functional requirement: allow operators to interact with online/offline information and enable data exchange via the cloud and 5G.
  (B) Functional block: test, diagnosis, and maintenance dimension block.
- Maintenance patterns and system failures;
  (A) Functional requirement: enabling comprehension and understanding of maintenance patterns and system failures using ML and NLP techniques.
  (B) Functional block: maintenance classification and pattern mining strategy development block.
- Feature extraction and fault mode classification;
  (A) Functional requirement: providing failure classification and sending maintenance notifications through the AR interface system.
  (B) Functional block: dynamic prediction algorithm block.
- Step-by-step directions;
  (A) Functional requirement: utilizing predefined rules and maintenance instructions to generate step-by-step directions for the operator.
  (B) Functional block: information integration flow model block.
- Supplementary interaction mode;
  (A) Functional requirement: enabling interaction mode for troubleshooting that does not interfere with maintenance tasks and fulfils the operator's need for intuitive and unobtrusive information interaction.
  (B) Functional block: information integration flow model block.
- Feedback for future maintenance improvements;
  (A) Functional requirement: document the impact of the recommended actions for future task improvements.
  (B) Functional block: diagnostics and troubleshooting block.

Table 7.3. The main functionality requirements for AR-based troubleshooting.

Function	Requirements	Applications
Cloud-based data fusion and analytics	Capturing maintenance procedural and rolling stock data from existing operations within a cloud-based environment [152], allows users to interact with digital information and enables data exchange via the cloud [198]	Gives the operator direct access to a real-time digital platform allowing the operator to interact with maintenance information
Natural Language Understanding (NLU)	Enable machines to comprehend and analyse maintenance patterns and system failures using ML and NLP techniques [197][30]	Analyse maintenance documentation, extract domain-specific entities from text, identify and classify entities in maintenance categories
Prediction model algorithm	Incorporating feature extraction and fault mode classification. The fault prediction module can output a predicted fault time and fault code for the rolling stock. If the rolling stock is in a faulty state, the fault prediction module will send a maintenance notification through the AR interface system [195]	Integrated cloud service in which operators with AR hardware can set ML parameters and access the prediction results through a human-machine interface
Augmented assistant	Utilizing a set of predefined rules and maintenance patterns, created by expert operators to cover a range of possible user inputs and scenarios, generate step-by-step directions to the operator [199]	Object recognition matches the input against the predefined rules and patterns to determine the appropriate maintenance response
3D Information presentation, interaction, and control	Enable supplementary interaction mode for troubleshooting which (1) does not interfere with maintenance tasks, and (2) fulfils the operator's needs for rich, intuitive, and unobtrusive information and interaction [200]	Information tool to enable operators to see detailed maintenance information by gazing/selecting upon the specific system attributes
Information exchange and feedback	Enabling feedback to the cloud-based information about the impact of recommended maintenance actions for improving future maintenance tasks [200][164]	Updated performance indicators are cucullated and sent back to the application

7.6.1. Data flow and mapping

To make AR-based troubleshooting as efficient as possible, best practices have to be in place. Therefore, this study proposes the data flow and data checklist required for AR-based troubleshooting in Figure 7.7.

Information and data must be collected from various sources, most frequent information from database management includes maintenance steps to be followed, machine status, and information collected from sensors [201]. Organizations should ensure that no access or security issues come up and software is working correctly to not affect the operator's ability to work. To help standardize and understand failure and maintenance data the process of connecting real troubleshooting procedures with real-time data is required [202]. Data mapping facilitates data migration, data integration, and data transformation and is needed for data management. Data loading is a process in which processed maintenance and system failure are moved to a designated interface [181].

Considerations such as where to move the information and how to use the information should be planned at the beginning of the transitory phase. AR applications may involve multiple devices, however, the most used visual devices are HHD, followed by HMD [201]. The high rate of HHD utilization can be attributed to their low cost, simple video see-through augmentation, and commercial availability, allowing early adoption. HMDs offer hands-free handling while performing maintenance operations contributing to ergonomic advantages. The choice of an AR device for troubleshooting system failures depends on several criteria, including its hands-free functionality, adherence to latency requirements, ability to provide 3D overlays, and the effectiveness of its ergonomic hardware and software design. It is crucial to consider these factors to ensure that the selected AR device meets the specific demands of troubleshooting tasks, providing a seamless and user-friendly experience for operators.

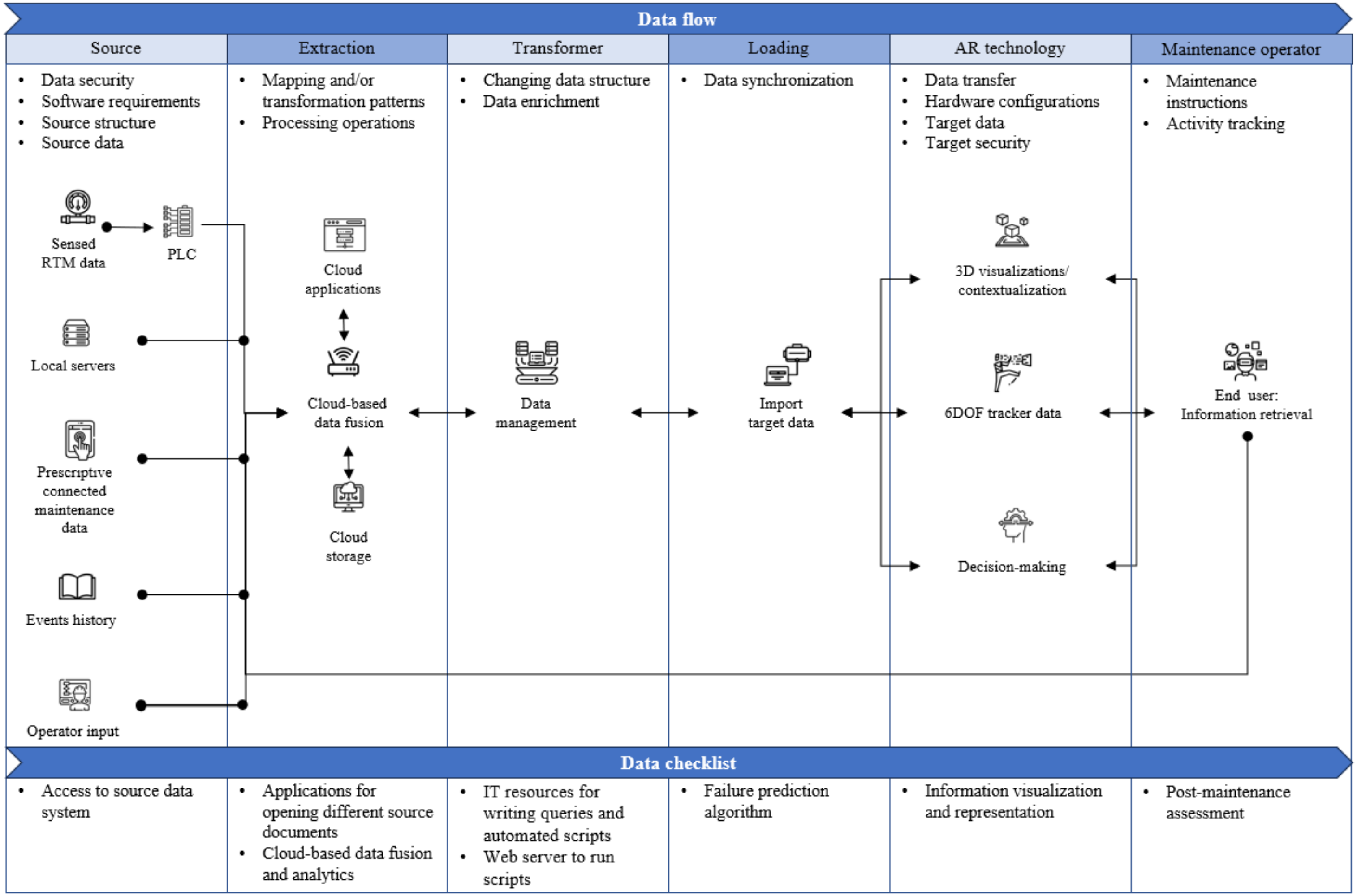

Figure 7.7. Data mapping and flow.

7.7 Railway case study

A sanitary system failure of rolling stock is solved using the SARA prototype to verify the functional building blocks for AR-based troubleshooting. The SARA prototype contributes to four industrial settings, namely: real-world annotation, contextual visualization, ensuring immersion to create troubleshooting experiences, and supplying the operator with accurate up-to-date maintenance information. Essentially, AR facilitates interactions with maintenance and system information that enhance maintenance operations. The incorporation of real-world annotation has the potential to substantially decrease cognitive load, offering operators a more streamlined and intuitive experience [203].

7.7.1. Troubleshooting scenario description

For this research, the sanitary system failure of the refurbished double-decker rolling stock (VIRM-1) is exploited. A comprehensive study has been performed in collaboration with NS on the sanitary system of the rolling stock [152]. The sanitary system failure has a major impact on rolling stock operations, as a train may not continue in service. Real-time monitoring and historical data reveal that this sanitary failure is in the top 20 most common system errors [204]. The sanitary system does not yet fully meet customer requirements, therefore, both the rolling stock manufacturer and NS are investigating the causes of the current problems. The case study highlights and presents the functionalities of an AR troubleshooting prototype and is validated by 11 maintenance operators. The functionality capabilities are then classified and mapped to the different functional blocks of the AR troubleshooting method.

The sanitary system failure addressed in this case study indicates that the pipe temperature in the bioreactor is too low and relates to the following issues: (1) risk of freezing, e.g. frozen pipes can lead to blockages, bursts or damage to the entire sanitary system, (2) the impact of the waste treatment system, e.g. functioning of the bioreactor can be affected, (3) the temperature regulation system, e.g. heating elements, temperature sensors, or control systems are malfunctioning, and (4) integration challenges, e.g. the failure can relate to communication or integration issues between the bioreactor and other related sanitary components. In any of the aforementioned causes, the low pipe temperature in the bioreactor coupled with the failing sanitary system requires thorough investigation and troubleshooting.

The workshop session (Table 7.2, session 3) revealed that the current troubleshooting strategy consists of calibrating temperature sensors, resetting toilet PLC, performing a service flush, and inspecting physical connections [204]. Data on diagnosing and performing maintenance actions to troubleshoot the sanitary system failure are collected from maintenance management systems and presented in Figure 7.8 and Figure 7.9.

The diagnosing stage in troubleshooting train failures (Figure 7.8) shows that the diagnostics are not pointing to a clear root cause of the failure. The majority of the failures disappear or multiple failures are present in the system, making troubleshooting even more complex. In addition, Figure 7.9 presents most maintenance actions involving resetting the toilet module or not even performing maintenance. The workshop session revealed that operators see the benefits of using AR for decision-making support, FTA, visualizing system components, and solving complex rolling stock failures.

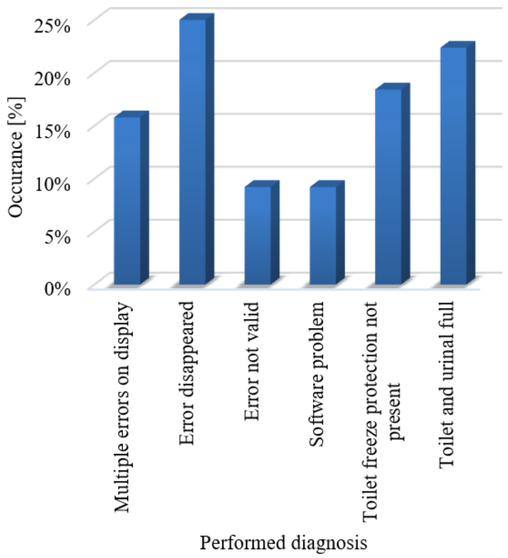

Figure 7.8. Diagnosis related to sanitary failure.

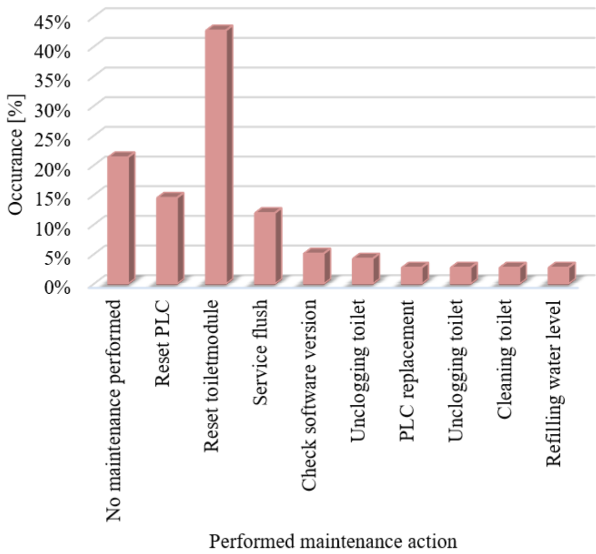

Figure 7.9. Maintenance related to sanitary failure.

7.7.2. SARA Prototype development

The SARA prototype is developed using a holistic design, illustrating how each functional block contributes to the enhancement of AR-based troubleshooting and the anticipated improvements in the existing troubleshooting procedures [205]. This comprehensive design strategy ensures a unified and synergistic integration of functional elements. The main task of the SARA prototype is to provide the operator with correct, complete, and real-time maintenance and system failure information and guide the operator through the troubleshooting procedure through AR. To do so, conceptual, embodiment, and detailed designs are developed [205]. All designs are built employing a 3D/AR Unity 2021.3.24f1 application in the HoloLens 2 to provide hands-free support. The conceptual design of the SARA prototype simplifies the sanitary system failure by superimposing and ensuring interaction with four sanitary subsystems tailored for an experimental mock-up, including a toilet controller, a bioreactor controller, a temperature controller, and a BID bioreactor. Real-time bioreactor pipe temperature data is collected from the VIRM-1, simulated using Arduino IDE 1.8.19 [206], and visualized in AR. The real-time data is simulated using Arduino, as a direct connection with the rolling stock was not feasible in this study.

Maintenance manuals incorporate the FTA provided by the company. The embodiment design of the SARA prototype expands the maintenance manual and FTA anticipates real troubleshooting scenarios and is designed to be tested on the rolling stock. The final detailed design includes all relevant maintenance procedural information and troubleshooting scenario characteristics.

To maintain the functionality and prevent not feasible changes to the troubleshooting procedure, the flow of the expected data collection and analysis, information integration, and information push of AR troubleshooting for the case study incorporates the requirements from Figure 7.7. The figure shows all the components needed for troubleshooting and supporting the SARA prototype.

7.8 Experimental results

The iteration of the design of the SARA prototype was done collaboratively with 11 sanitary and troubleshooting experts from NS (Table 7.2). Before the evaluation of the subsequent prototypes, a short introduction to the research project and the developed AR-based troubleshooting prototype was provided to the operators. The operators then performed the troubleshooting exercise utilizing the SARA prototype. After completion of the troubleshooting exercise, the operators were interviewed using semi-structured interviews to determine the quality of functionalities for troubleshooting sanitary system failures. Each test takes approximately 30 minutes per person, followed by 20 minutes of semi-structured interviews.

After testing the conceptual design (Figure 7.10), the researchers observed that the maintenance guidance and system failure information are up-to-date. Real-time temperature data is presented to the operator and reflects what maintenance activities are required to troubleshoot the failure. Although the troubleshooting prototype is complete by presenting all relevant information, the operators find that the experimental mock-up does not reflect an actual troubleshooting scenario. In addition, the visualizations are sometimes perceived as blurry and require eye calibration for all operators individually.

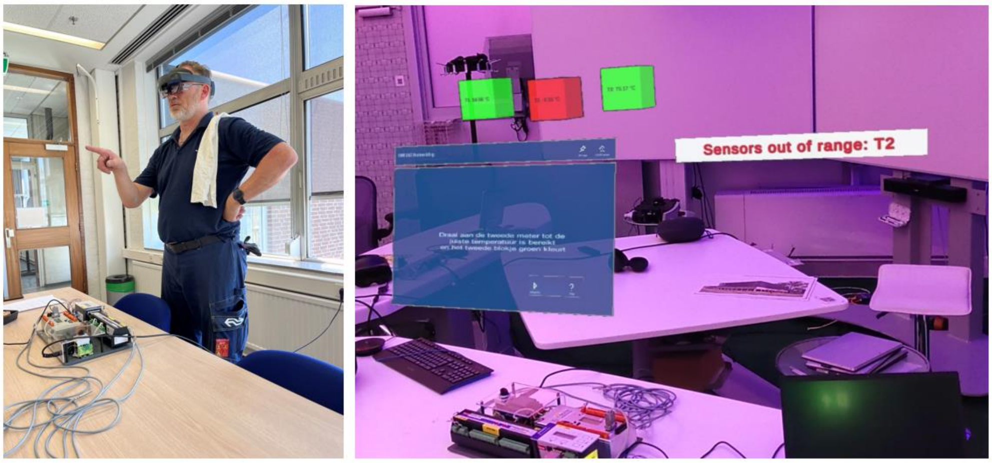

Figure 7.10. Conceptual design SARA prototype.

After testing the embodiment design (Figure 7.11), the operators perceived the AR prototype more positively because of its direct application on the rolling stock. The FTA is extended and includes calibration of the temperatures to solve the sanitary system failure and contribute to a realistic problem-solving strategy. The semi-structured interviews revealed that the 3D visualizations are presented in the same way and are perceived as intuitive, straightforward, and clear.

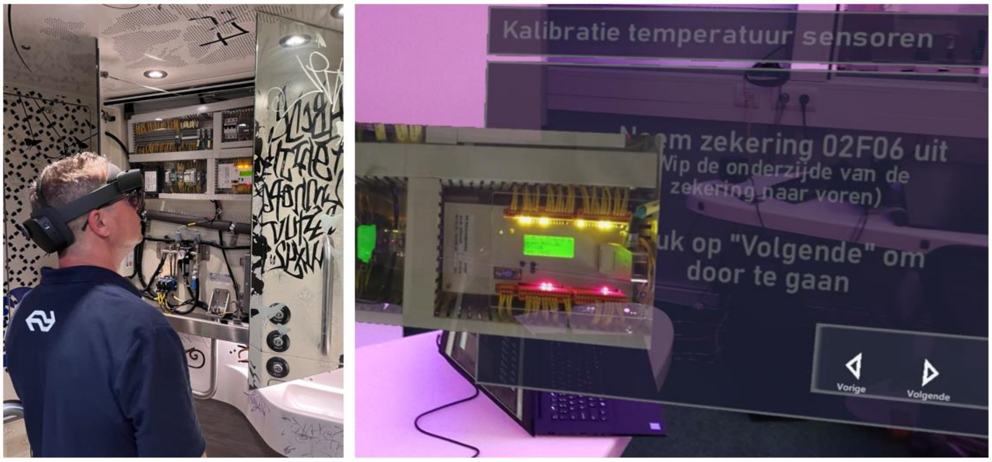

Figure 7.11. Embodiment design SARA prototype.

After testing the final detailed SARA prototype (Figure 7.12), remarks for further SARA prototype developments include: (1) establishing a live connection with the rolling stock instead of simulating real-time system data, (2) monitoring and tracking maintenance activities to document the procedures, and (3) capturing operator feedback to integrate expert knowledge into the system. The final functionalities of the SARA prototype include (1) 3D visualizations and superimposing of sanitary components, (2) interaction and manipulation of 3D objects, (3) real-time monitoring of bioreactor pipe temperature, (4) provision of supportive materials (images of sanitary components), (5) analysis of system failure, (6) synchronization of the virtual and real world, and (7) guidance of real-time maintenance, troubleshooting, and system information support.

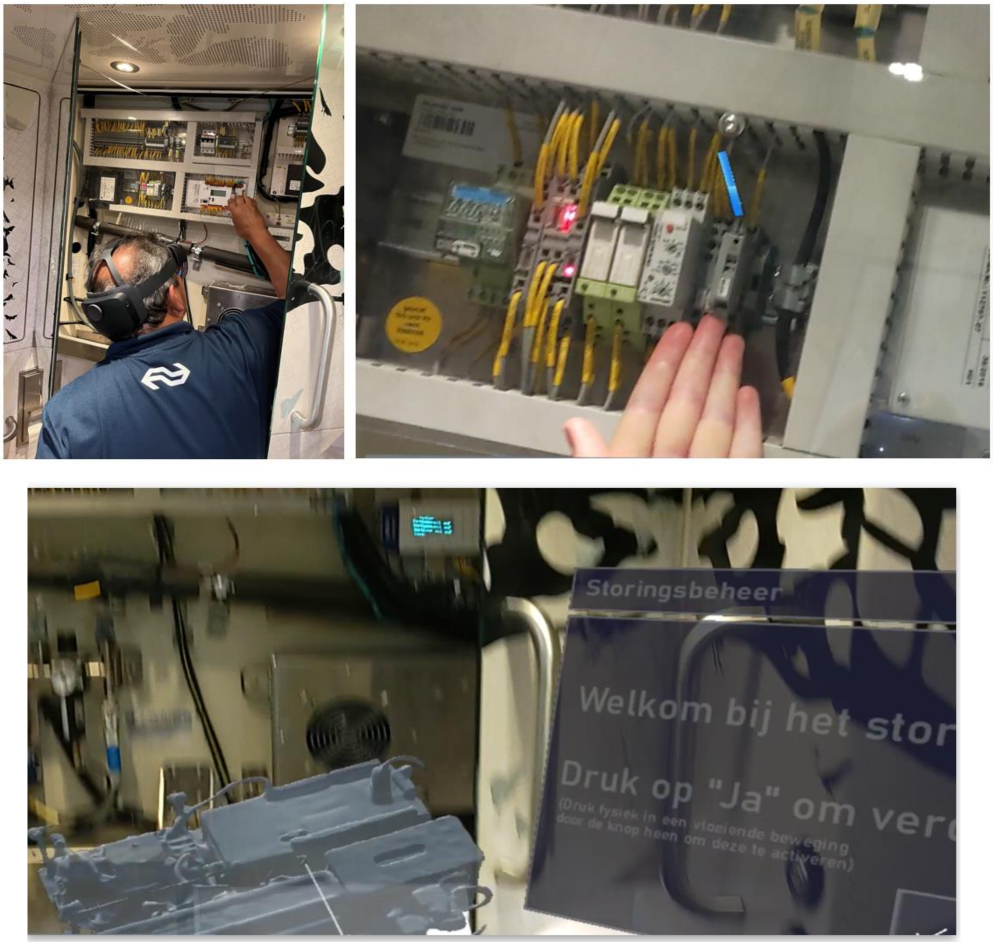

Figure 7.12. Final SARA prototype.

7.9 Discussion

The presented research provides insight into the functional blocks required for AR-based troubleshooting for solving rolling stock system failures. Emphasizing the research question, functional blocks are not only presented but also validated by operators through the design of an AR-based troubleshooting prototype. The outcomes highlight the significant troubleshooting capabilities, particularly involving a sanitary system failure. A detailed overview of the functional blocks and their impact on troubleshooting is summarized in Table 7.4.

Table 7.4. Major impacts of AR-based troubleshooting in the railway industry.

Functionality	**Impact on AR-based troubleshooting**
Cloud-based data fusion and analysis	Access to real-time online and offline maintenance and failure data
Maintenance information classification and pattern mining	Cleaning data and organizing maintenance information
Fault analysis and prediction	Clarifying the root cause of the problem and connecting corresponding maintenance activities
Information integration	Contextualizing and synchronizing maintenance and system failure information
Diagnosing and troubleshooting	Supporting operators in decision-making strategy by visualizing 3D maintenance information

However, certain objectives have encountered challenges within this research scope. Establishing a direct connection between rolling stock and the AR-based troubleshooting tool has proven unattainable, necessitating the simulation of real-time data. significant challenges also arise in ensuring compatibility with existing systems and managing data effectively. The seamless integration of real-time maintenance data is acknowledged as crucial. RCA relies on standardized company FTAs, with an ideal approach involving automated fault detection using historical data. This ideal scenario calls for the establishment of a centralized, cloud-based system linking databases and implementing prediction algorithms. The creation of a virtual overlay in the study involves building a 3D model, with the optimal method being the utilization of object recognition for the identification and continuous tracking of real-world components.

A generalizable causal relationship between the use of AR functionalities has not been established. In the case study, cloud-based information management systems are not connected to maintenance data by exploiting ML techniques for failure selection and filtering purposes. Through prototyping, real-time bioreactor and sanitary data with existing FTAs and maintenance manuals are integrated. This integration is enhanced by combining the data with 3D visualizations, offering maintenance operators immediate maintenance support.

AR prototyping highly depends on the hardware and software selection, as the network connectivity can impact the effectiveness of the troubleshooting solution. During the tests, network issues emerged, leading to the repetition of the test or resulting in the delivery of blurry and unstable 3D visualizations. Environmental conditions, e.g. high temperatures observed during the tests, created reluctance among some operators to use the HMD in the summer.

The results presented, although insightful in the context of a prototype evaluation, have limited statistical power. This means that the ability to detect true effects or differences in troubleshooting may be compromised. The small sample size of 11 participants may limit the generalizability of the findings. The insights gained from the small group may not represent the maintenance and troubleshooting community and increase the risk of bias. However, by incorporating qualitative methods, valuable insights that complement the data coming from the small sample size is provided. To address the limitations of the small sample size, future research could prioritize expanding the participant pool and diversifying demographics to enhance the statistical power and generalizability of the findings.

7.10 Conclusion

Traditional troubleshooting methods often involve manuals, technical documentation, and the knowledge and expertise of operators. The advent of AR has revolutionized the way maintenance teams approach troubleshooting and requires functional blocks for a comprehensive understanding of complex troubleshooting procedures. The functionalities of the troubleshooting prototype supported operators by giving contextualized 3D visualizations, real-time data support, enabling interaction and control, and up-to-date maintenance instructions. Although the prospects of AR-based troubleshooting are positive, challenges and considerations remain.

Future work can include a larger sample size and a thorough statistical analysis of the presented functional blocks' effect on AR-based troubleshooting to improve the generalizability of the results. Moreover, conducting longitudinal and cross-sectional studies can further explain and improve the industrial impact of the troubleshooting strategy.

The gained insights on AR applications, troubleshooting functionalities, and requirements demonstrate the added value of this research for the maintenance and industrial research community. It underlines the potential of AR-based troubleshooting in an industrial setting and sheds light on technologically impactful ways of developing such customized industrial solutions. Moreover, to increase the perceived usefulness, this research underlines the importance of collaboratively designing prototypes with operators. To conclude, the presented functional blocks form the basis of an AR-based troubleshooting tool that can support operators in maintenance work and has scalability opportunities for future problem-solving operations.

Chapter 8 – Developing AR design guidelines for troubleshooting rolling stock system failures: Industrial prototyping and human factors

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8.1 Theme IV: Functionality of AR troubleshooting

The maintenance operator evolved into an experienced and skilled individual with enhanced physical, sensory, and cognitive capabilities through Industry 4.0 technology integration, requiring tailored-based troubleshooting support to reduce physical and mental stress. AR is part of the human-centred-multi experience, and the rapid advances in the technology applications attract incorporating it in the troubleshooting workflow of maintenance operators. Integrating real-time data infrastructure and tailored-based information in the UI is key for effective human-AR collaboration. Existing research lacks troubleshooting support to contextualize, visualize, and structure real-time rolling stock system failures. AR Design guidelines aim to converge the technology with the human-centred fault-diagnosing domain. This research develops high-level AR design guidelines for troubleshooting rolling stock failures by providing functional and UI experience requirements utilizing operator input and prototyping methods (Figure 8.1). A railway case study shows how the AR design guidelines support operators in structuring and contextualizing data and decision-making strategies.

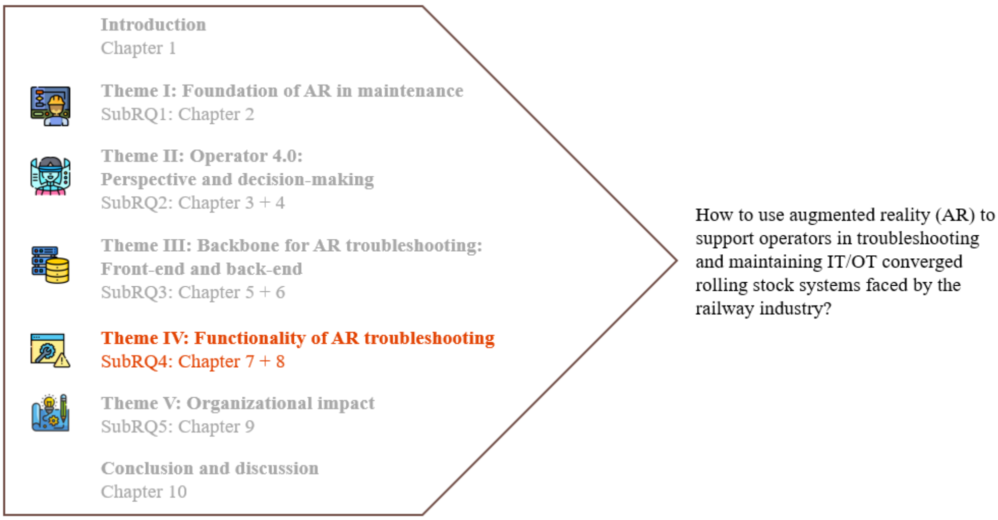


Figure 8.1. Theme III: Backbone for AR troubleshooting: Front-end and back-end.

8.2 Introduction

The digitization and modernization of rolling stock challenges the accuracy, efficiency, and effectiveness of maintenance and troubleshooting procedures. Maintenance and troubleshooting technologies ensure the safety of rolling stock during operations [169]. Maintenance operators work in highly changing complex environments and constantly adapt their problem-solving strategies, gaining benefits from automation and robotization while achieving greater autonomy [207][208]. Operators have a crucial role in maintenance operations caused by high-precision tasks [209], enabling human-technology interdisciplinary cooperation [210][211]. Rolling stock systems are complex, and timely identification and resolution of issues are critical to prevent disruptions and downtime. The focus on rolling stock system failures necessitates the integration of domain-specific data, such as train diagnostics, sensor data, and historical performance metrics, requiring tailored solutions for the unique challenges of rolling stock.

AR is a technology in which digital elements are merged with the physical world. AR has great potential to support operators in their daily work by visualising maintenance tasks and rolling stock information, thereby contributing to troubleshooting complex failures, knowledge transfer, and reducing operational errors [212]. Industrial application scenarios for AR are maintenance, teaching, and training in which operators follow step-by-step guidance to fulfil tasks by superimposing virtual objects on physical systems [213]. The attraction and attention of users are caused by the proven usefulness in diverse engineering scenarios, the integration in the workflow, and the interactive tools, interfaces, or functionalities that facilitate user interaction and enhance overall utility. It is important to highlight that AR has always been a human-centric technology [214]. The human-centric concept can be reflected in designing a user-friendly maintenance and troubleshooting workflow and ensuring the operator's safety to the greatest extent possible [214]. A recent trend seen in the industry is the emphasis on human factors in supporting operators while troubleshooting failures in maintenance operations, often involving AR interaction [130][171]. Human factors in maintenance still seek (1) a clear understanding of operator needs, e.g. connection of different geographic entities, such as people, sensors, data, and devices, (2) adopting different interfaces for interactions in AR, e.g. operator perception and input to a system or a coworker, and (3) guidelines for content authoring [215][201].

AR troubleshooting can help meet industrial human needs from higher levels by transforming interactions between operators and rolling stock or operators and the maintenance and troubleshooting environment to enhance mutual cognition and trustworthiness, which is a mutual reinforcement for the self-fulfilment of humans and growth in the rolling stock industry. Moreover, AR troubleshooting allows for real-time visualization of system components and historical data about the rolling stock system's performance, enabling operators to quickly identify and address issues. Advancements lie in addressing challenges posed by the integration of mechanical components and digital systems within the AR troubleshooting framework. Designing an AR UI resulting in seamless transitions between dynamic troubleshooting procedures and standardized maintenance work presents a novel challenge and contribution. AR-based troubleshooting has three functionality requirements [130][171]: (1) fault detection, recognition, and identification, (2) providing a problem-solving strategy, consisting of existing maintenance procedures and fault analysis, and (3) visualizing and contextualising the rolling stock system failure through AR. While abundant efforts have been made to design UI heuristics [216][217][218][219], there is a limited understanding of what AR UI holds for industrial cases. Understanding how users interact with AR interfaces during troubleshooting tasks, including their cognitive load, navigation patterns, and preferences for presenting diagnostic information is understudied. In addition, the full exploration of combining real-time data integration with industrial applicability while incorporating human factors remains incomplete. Considerations for visual design, information organization, and interactivity to support efficient problem-solving require developing design guidelines for best practices for creating AR interfaces optimized for troubleshooting scenarios. Establishing consistent and harmonious designs that account for human factors is essential in designing the UI of an AR troubleshooting tool.

The goal of this work is to understand and develop AR design guidelines for troubleshooting strategies in industrial applications. Table 8.1 synthesizes insights from existing literature, outlining the identified needs and empirical findings relevant to each aspect addressed in this work [169][214][220][221]. To address the research gap concerning human factors in maintenance and AR UI design with troubleshooting functionalities, this work presents three aspects for developing the AR design guidelines: (1) functional requirements, (2) operator role, and (3) UI experience. The functional requirements focus on collecting, processing, and structuring all relevant maintenance and system failure data, diagnosing the system failure, and presenting the maintenance activities [169]. One key consideration in the mainstream use of AR is the need for a suitable AR UI that allows operators to interact with and control the virtual content [220]. The AR UI presents the maintenance information intuitively and reflects on its usefulness, application use, and hardware capabilities. In the futuristic human-centric industry paradigm, the well-being of operators will be put at the central place [214]. The operator influences the development of the AR design guidelines given their troubleshooting knowledge, and experience and influences the technology adoption [221]. Real-world validation ensures that the proposed AR maintenance and troubleshooting guidelines are tailored to the challenges faced in the rail industry.

In summary, solving AR troubleshooting challenges for rolling stock system failures is important because it enhances operational efficiency, standardizes maintenance practices, and positions the industry for continued innovation and competitiveness on a global scale. The broader industry benefits from improved reliability, reduced maintenance costs, and a more sustainable and technologically advanced approach to rolling stock maintenance operations. This work contributes to the field by offering a comprehensive set of design guidelines specifically tailored for AR UI aimed at troubleshooting rolling stock system failures and improving maintenance procedures through the integration of human factors. Drawing from a thorough review of the literature, this research contributions extend to several key areas. The primary focus is on presenting a robust set of design guidelines. These guidelines encompass various aspects, including data collection, processing, and storage, and integrate sophisticated techniques such as case-based reasoning, maintenance pattern mining, and contextualization and visualization of maintenance information. This work plays a pivotal role in shaping functional requirements for AR UI design, showing how interfaces contribute to the creation of shareable and scalable AR applications by addressing real-world troubleshooting scenarios. Three AR troubleshooting prototypes to refine and validate the efficacy of the proposed design guidelines are developed. The inclusion of a case study conducted within an industrial setting provides valuable insights into the practical requirements and challenges encountered by operators during the troubleshooting of rolling stock systems. Operator feedback ensures that the design guidelines align with the practical needs and preferences of the end-users.

Table 8.1. Identified needs and empirical insights for AR design guidelines.

UI requirements	Functional requirements	Operator (human-centric) perspective
• Utilize AR overlays to display relevant information directly on the physical components being analyzed • Incorporate multimodal interaction; voice, gestures, and touch interactions • Allow operators to customize the AR interface based on their preferences and job roles • Use spatial awareness to organize data logically within the AR environment	• Ensure seamless integration with existing rolling stock systems • Provide real-time data on the performance of different components and systems • Enable operators to visualize critical parameters, diagnostics, and alerts instantly • Develop AR interfaces capable of identifying and prioritizing faults based on severity and impact on overall system performance • Enhance fault prediction accuracy	• Design user-friendly and easy-to-use AR interfaces for operators with varying technical backgrounds • Implement natural user interactions for a seamless experience • Include onboarding processes that account for different levels of expertise among operators • Minimize cognitive workload by presenting information in a clear, concise manner • Implement feedback mechanisms to gather input from operators regarding the effectiveness of the AR troubleshooting system

8.3 Related work

Although numerous approaches are contributing to the field of AR maintenance support, there is a small amount of research work done on the provision of real-time support [222]. Related work presents a framework aimed at creating interactive, intuitive, and collaborative channels between shop floor technicians and expert engineers remotely via AR [223][224]. However, operator support is provided through remote instructions rather than relying on an independent AR troubleshooting system. Recent research utilizes real-time historical data accessed through cloud hosting can facilitate remote predictive analytics [225]. More research is required to minimize the need for human interventions in the troubleshooting process. Specific requirements can be identified for AR applications related to the variance of products and processes, work conditions, data connection issues as well as media literacy and technology acceptance [226]. Concerning reliability, adherence to work safety regulations, and the precision of system overlays, there are notable challenges to overcome. Requirements for the development of AR systems for industrial use have to be identified within the context of the troubleshooting applications. While previous work has laid the groundwork for AR maintenance and troubleshooting across various industries [37], the specific focus on rolling stock system failures introduces novel insights and advancements. This targeted approach to designing guidelines for AR troubleshooting addresses the intricacies of the rail industry, offering specialized solutions that go beyond the scope of existing case studies in a more generalized industrial context.

The world of transport is undergoing a digital revolution, and the railway industry's existing maintenance strategies need to reduce the work complexity that arises from troubleshooting IT and OT converged system failures [227][98]. As noted [171], there is a need for tools that can conceal these complexities from human agents and help them troubleshoot complex system failures. Furthermore, [171] noted that the tool must offer decision-making support utilizing contextualizing, visualizing, guiding, and tracking activities for maintenance operators. Previous work has laid the foundation for developing a troubleshooting support tool with AR decision-making that supports operators in their work. In this work, the decision-making process is supported by high-level AR design guidelines for troubleshooting by setting functional requirements and stating UI experience design heuristics using operator input.

The related work is centred around key areas including UI experience for increasing technology acceptance of AR, the functional components needed to troubleshoot complex rolling stock failures, and human factors to discuss the operator's role in developing the design guidelines.

8.3.1. Functional components AR troubleshooting

Several studies have worked on troubleshooting maintenance problems using AR [228][229]. While most research efforts focused on exploring ease of use, tool usability, and remote support, there is still a gap in exploring complex real-time task support, connectivity and accessibility, and operator integration in industrial applications. Some work investigated maintenance support in industrial environments by developing prototypes to perform image recognition and transferring existing maintenance manuals to the AR instruction system [230][231]. They show that augmented instructions improve speed and reduce errors in problem-solving, especially by localization and selecting system components. However, the human factors remain underexposed because most work is focused on the technical capabilities of the technology [232][224].

Recent studies show the components required for troubleshooting maintenance failures in AR [171] consist of (1) having a centralized data collection platform for collecting, filtering, and structuring all maintenance failure information, (2) offering problem-solving (troubleshooting) capabilities by performing root-cause analysis,

(3) visualizing and contextualizing information for providing system reference by object recognition and capturing maintenance activities, and (4) enabling dynamic decision-making by giving step-by-step AR instructions to the operator. This work preserves AR capabilities for troubleshooting, e.g. superimposing 3D maintenance manual visualizations in existing industrial environments, while integrating human factors.

8.3.2. UI experience in AR

The use of UI design principles in AR applications for railway maintenance is an emerging area that has received limited attention in the existing literature. While some research efforts have focused on creating interactive and intuitive channels between technicians and expert engineers via AR, these primarily involve remote instructions rather than independent AR troubleshooting systems. In the broader context of industrial AR applications, previous research has laid the groundwork for maintenance and troubleshooting across various industries. Key areas of focus in related work include UI experience to enhance technology acceptance, functional components for troubleshooting complex failures, and human factors to incorporate operator perspectives into design guidelines.

Several researchers have explored design guidelines in AR environments. The guidelines for utilizing AR in maintenance are mostly related to the usage of visual aids, mental model building (e.g. the user's internal representation of a task), authoring tools, ease of use, information display, and interaction with the virtual data displayed [233][234][235]. The general concept is that AR technology intuitively conveys the maintenance tasks. The work of Eze and Crick (2023) [236] discusses a set of guidelines for the systematic design of AR for Human-Robot Interaction systems. In the paper, the design representations for the robot trajectory over the baseline approach are intuitively conveyed to the human. However, in this work, the operator's perspective is limited to the cognitive workload performance.

The context-dependent characteristics of an AR experience provide opportunities to design guidelines for troubleshooting system failures. The development of a set of usable design heuristics for UI experience in AR is needed to identify usability issues early in the product development cycle [237]. A review of the applicable literature reveals that many AR heuristics focus on specific applications of AR technology, namely mobile or smartphone AR devices [216], or more general principles or design features of the AR design space [217]. While these provided valuable insight into various aspects of AR design evaluation, they lack simple application to current ongoing design principles [218]. Table 8.2 presents a summary of design heuristics for UI experience in AR drawn from literature, along with its corresponding impact. While previous studies have offered insights into various aspects of AR design evaluation, they often focus on specific applications or general principles that may not directly translate into ongoing design practices. Recognizing this gap, the selected AR design heuristics for the table are chosen for their relevance to UI experience in AR and their potential impact on design effectiveness. Each heuristic is carefully selected to address crucial aspects of AR UI design, considering factors such as alignment with the physical environment, communication interaction, minimalistic design principles, capabilities for recognizing, diagnosing, and recovering from errors, documenting and providing sustainable relief for operators, minimizing physical effort, ensuring system recognition, and accommodating hardware and software limitations. These heuristics are deemed important for designing AR interfaces that effectively support troubleshooting tasks while considering human factors and usability. By presenting these heuristics in Table 8.2 alongside their corresponding impacts, the aim is to provide a concise yet comprehensive overview of key considerations for UI experience in AR, facilitating their application in ongoing design processes and contributing to the advancement of AR technology in practical settings.

Table 8.2. Design heuristics for UI experience in AR.

AR design heuristic	UI experience in AR	Impact
Alignment of the physical and virtual world: user environment, perspective, and task	Virtual alignment with the physical object should be continuous over time [218]. Visualizations must match the mental models that the operator has based on their physical environment and task and should behave as realistically as possible by being proportional to the physical environment [216][218].	Provides a realistic troubleshooting scenario where the operator must interact with both the virtual and real world.
Communication interaction	Gestures used to translate, rotate, and interact with virtual objects should be user-friendly and designed consistently [216] [219].	The operator manipulates the virtual object with ease and is useable from different viewing angles, distances, and movements of the end user.
Minimalistic design: minimize distraction and overload	The system should not show unfiltered information to the operator. Overly cluttered information overwhelms the end user [218]. Operator input is needed for colour, motion, distance, and resolution design solutions.	Giving minimal pre-sorted information ensures maximal information transfer while reducing mental overload.
Recognizing, diagnosing, and recovering capabilities	Information to prevent, diagnose, and deal with errors should be provided to the operator [217][219].	Status update of the task is key to providing the operator with troubleshooting information.
Documenting and sustainable relief	Appropriate help regarding the system, tasks, and elements should be available to support the operators [217].	By automatically documenting and storing information [238], the operator needs to perform fewer administrative tasks, increasing sustainable relief.

AR design heuristic	UI experience in AR	Impact
Physical effort	Placements of virtual elements should not require the operator to perform actions that are physically challenging or dangerous [218]. Optimally, the task should be completed with the smallest number of interactions to achieve a more efficient experience and diminish the fatigue felt by users [217].	Simplifying maintenance tasks ensures efficient information transfer and reduces the physical effort required. The operator should recognize and understand a situation or environment and identify possible threats.
System recognition	Actions related to virtual objects should be visible when adding to a scene. The virtual object should represent the object under investigation [216] [239].	Recognition of the system provides system context and specifications to the operator.
Hardware and software design	UI experiences in AR should be designed to accommodate the capabilities and limitations of the hardware and software platform [218].	General solutions increase the scalability and applicability of the design.

8.3.3. Human factors: the operator's role

Exploration of how humans perceive AR information goes back several decades. Especially within the current human-centric research lines, AR embraces the potential to integrate operators into the new generation of Human-Cyber-Physical Systems (HCPS) [240]. AR includes operators in HCPS in a way that aspires to improve their safety and health, leverages their cognition and intelligence, and inspires innovative maintenance operations, resulting in strengthening staff well-being and industrial growth. However, applications present the virtual objects or maintenance data separately from the physical model and therefore not represent accurate on-site visualization [188]. The minority of the case studies presented in related work include the human interaction with AR control, configuration, and real-time information tailored to the operator's perspective (e.g. capability expectations and current maintenance task). During troubleshooting rolling stock system failures, technical manuals and real-time system information guide operators to carry out tasks. However, it is time-consuming for operators to consult various forms and structures of technical information from a plethora of technical manuals. Therefore, a centralized data storage platform connected to AR UI must become accessible for operators to replace printed and local-stored manuals. The characteristic of a centralized data storage platform lies in its ability to select, filter, and sort all data based on the operator's needs and preferences, integrating AI methods [241][242]. To utilize AR as a cognitive assistant, the safety-critical thinking process requires access to current status details, performance metrics, contextual real-time system information, human-technology interaction and collaboration, as well as activity tracking [243][244]. Further exploration of prototypical implementation and evaluation is still required.

From a cognitive load viewpoint, communicating real-time data is key in AR systems to dynamically and sequentially change spatial components [245]. More intuitive and seamless interactions are explored in this real-world industrial paradigm by incorporating human factors.

Various studies show a common finding in human-computer interaction (HCI), interactivity positively affects the assessment of a UI experience [217][246]. The effect of UI in virtual environments reveals that technologies with high levels of interaction improve subjective user experience and objective usability [247].

8.4 Methodology

This work is based on previous AR support tools across different application scenarios [171][238] and offers holistic design guidelines for crafting an AR UI experience that enhances human factors. The work directly contributes to the design of applied industrial AR solutions, with AR design guidelines serving as the foundation for an AR troubleshooting tool. These guidelines, developed through a human-centred design approach, consider functional requirements and AR UI aspects. The development process of AR design guidelines consists of three iteration stages (1) the initial stage, for creating awareness, interest, and value of troubleshooting rolling stock failures among management and operators using AR to establish initial AR design guidelines, (2) hand-over stage, for defining a use-case for troubleshooting, developing the exploratory prototype, and tailoring the AR design guidelines based on operator input, and (3) practice stage, for iterating the experimental prototype to the evolutionary prototype by conducting experiments in real-life troubleshooting scenarios and collecting user experience and conducting usability assessment. The development process ensures that the tool is designed appropriately for new and experienced users and provides a systematic approach for the researcher towards designing AR troubleshooting tools. Validation occurs through the creation of an interaction process of three AR troubleshooting prototypes, subsequently validated in an industrial case study with the NS. The study emphasizes the integration of AR systems into everyday work, addressing the HCI community's lack of guidelines in this area [248][249]. The research framework is grounded in well-known methodologies, ensuring a robust foundation [242][203][250].

8.4.1. Prototype development process

The prototyping methodology aligns with the principles of the iterative design process [251], where multiple prototypes play a vital role in refining the tool's functionality [252]. The prototyping process is structured into three phases (1) an exploratory prototype that focuses on the early stages of the design, presenting the function of the tool, (2) an experimental prototype to obtain feedback from the operators, emphasizing technical aspects, and (3) an evolutionary prototype developed to interact with an actual troubleshooting scenario, showcasing real-world application. The prototype development process involves defining the requirements of a troubleshooting use case, developing a basic prototype incorporating the UI and functional requirements, performing preliminary testing, refining the prototype, and final testing and considering adoption. Throughout this process, operators actively engage in testing and reflecting on each prototype, providing valuable feedback. This iterative approach involving three prototypes ensures that operator insights contribute to the improvement of both the AR design guidelines and the evolving prototype (Figure 8.2). Three iteration rounds are considered sufficient to develop AR design guidelines for troubleshooting system failures as they allow for iterative refinement and comprehensive feedback collection.

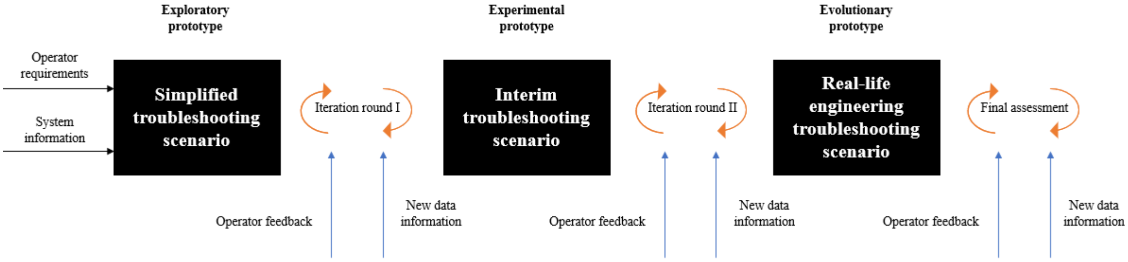


Figure 8.2. Prototype development process.

8.4.2. *Participants and setting*

To validate the prototypes in the case study, 11 participants experts in troubleshooting rolling stock failures were recruited. For statistical power analysis and evaluating the number of participants in the experiment, the G*Power is used [253]. G*Power statistical test is commonly used to investigate the decision-making process of individuals and is therefore applicable in this socio-technical context. In the prototype testing, a priori power analysis for one group t-test requires a one-tailed test, a specification of Cohen's effect size measure d of 0.5, a significance level α of 0.15, and results in a sample size of 15 [253]. Due to the specialization of the work area, a sample size of 11 is sufficient [254].

The validation of the prototypes will be conducted in several sessions at NS' maintenance facilities in Maastricht and Onnen in The Netherlands. The maintenance workshops have all the equipment necessary for troubleshooting. In addition, real-life rolling stock system failures can be simulated at these maintenance locations.

8.4.3. *Human-centred qualitative field study approach*

The human-centred design approach, employed in this study seamlessly integrates bottom-up technology design approaches and incorporates participatory design principles. The participatory design approach emphasizes establishing a collaborative design effort with operators and the designer through prototyping [255]. Meanwhile, the human-centred design approach focuses on the operator's perspective to create valuable and usable solutions [256]. In this work, the design process actively encourages collaboration between designers and operators, fostering the development of AR design guidelines through the prototyping of an AR troubleshooting tool.

The qualitative field study starts with a semi-structured interview, utilizing the HoloLens 2 to gauge operator AR knowledge and troubleshooting strategies (Table 8.3).

Table 8.3. Set of questions to determine operator AR knowledge and current troubleshooting strategy.

Set of questions oriented to determine AR knowledge	Set of questions oriented to the current troubleshooting strategy
• What existing knowledge and/or experience do you have with AR? • What is your opinion on using AR for troubleshooting support?	• How are current rolling stock system failures being resolved? • What information sources do you consult for troubleshooting and what information are you missing while troubleshooting?

Ethnography and research on rolling stock maintenance, alongside semi-structured interviews during the prototype assessments (Table 8.4), offer a comprehensive understanding of operator perspectives on AR UI and functionality requirements. The alternating sets of questions ensure a thorough exploration of the participant's experiences and expectations.

Table 8.4. Two sets of questions asked during the prototype assessment interviews with operators.

Set of questions oriented to the AR UI of the prototype	Set of questions oriented to the functionality requirements of the prototype
• How are the 3D superimposed and 2D visualizations being experienced? (e.g. 3D object alignment and usefulness) • What kind of visualizations will support you better in the current troubleshooting prototype? • What is your opinion about the design of the AR maintenance manual? • What hardware limitations do you perceive while troubleshooting?	• What is your opinion about the quality and accuracy of the failure and maintenance information? • How do you perceive the AR problem-solving strategy? • What failure data and maintenance information is missing and needed for troubleshooting? • What are your findings about automatically storing maintenance information, and how would this benefit your problem-solving strategy?

Operator input, collected through semi-structured interviews, is processed using ATLAS.ti, enabling an inductive analysis of the entire dataset [257][45]. This approach uncovers trends related to functionality requirements and AR UI preferences, ultimately informing the development of AR design guidelines. The iterative nature of prototyping, coupled with human-centred design principles, ensures that the resulting AR troubleshooting tool is not only technologically sound but also aligns closely with the operator's needs and preferences.

8.5 AR design guidelines development process

Figure 8.3 presents the development process of AR design guidelines. To understand the AR troubleshooting UI experience requirements and determine its functional capabilities, simplification of the actual scene and having a sample implementation is key. The intuitiveness that AR in prototyping adds to the perception and interaction of users provides further motivation for its implementation. Although there are many interesting applications of AR technology trying to explore the potential of AR, very few are convincingly embedded in AR solutions in prototype development processes [251]. This work develops multiple AR troubleshooting prototypes and tests their functionalities in laboratory settings and real-life troubleshooting scenarios to achieve a dynamically adjustable UI experience in AR. The AR design guidelines provide input to the various iteration stages and receive feedback from operators for further development.

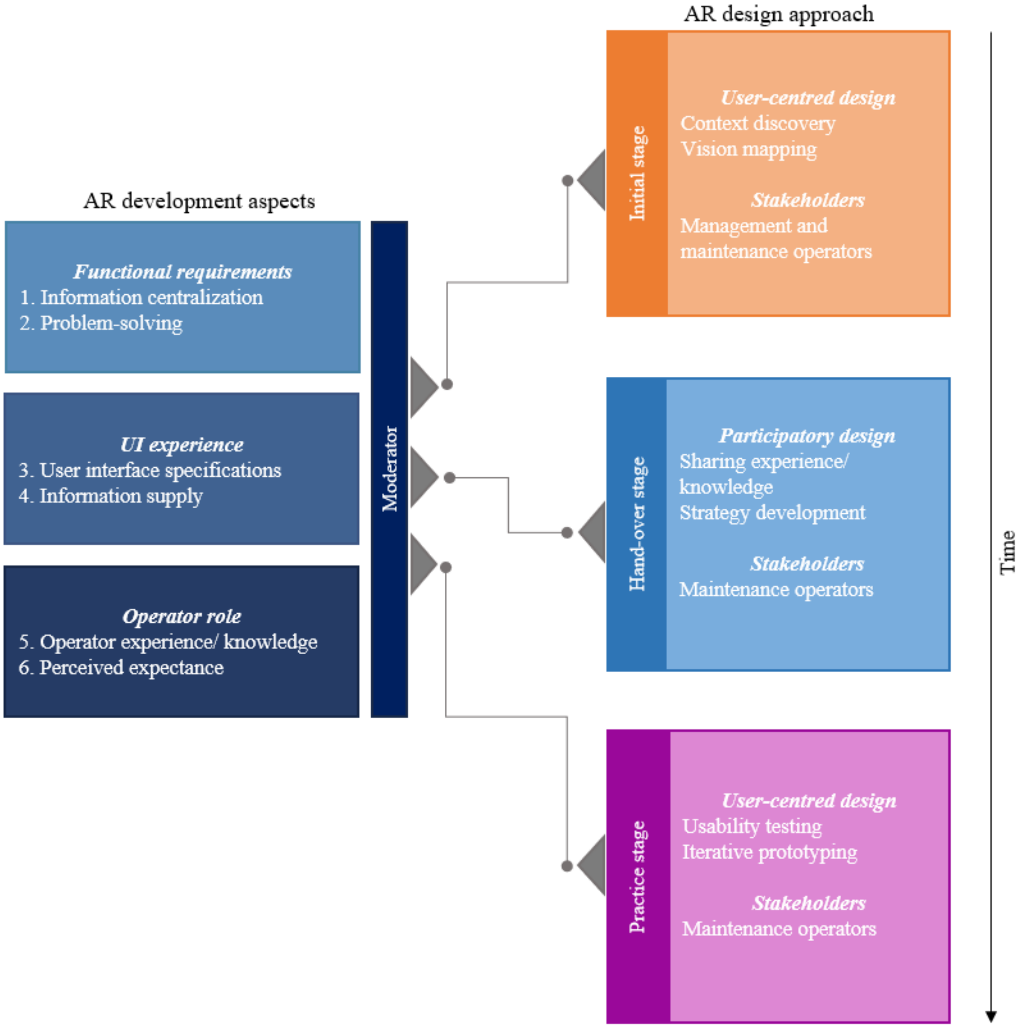


Figure 8.3. AR troubleshooting design guidelines development process.

8.5.1. Functional requirements

The AR troubleshooting system adopts a data-oriented UI paradigm by effectively organizing, presenting, and utilizing data essential for effective decision-making within the context of Industry 4.0 [171]. It is equipped with sensing capabilities and structured data visualization functionalities to enhance its effectiveness [125]. The system's technical capabilities are defined by the following functional requirements:

- Real-time data collection and structuring: The system is capable of capturing and organizing data promptly, ensuring that the information is current and up-to-date. The system collects, structures, and extracts both online data, which is collected directly from ongoing operations, and offline data, which is collected from historical maintenance records. This includes information on system components, diagnostics, and performance metrics. Utilizing sensors embedded within the rolling stock supports the collection of real-time operational data, whereas data logging and manual input allow operators to manually input data, and observations, into the system during troubleshooting activities. Storing the organized data in a centralized database or data repository supports easy access, retrieval, and analysis of information.

- Failure data extraction for data mining: The system extracts and categorizes rolling stock system failures, preparing the data for further analysis using data mining approaches. Categorization supports grouping similar types of data into categories or data structures based on predefined criteria. This step involves organizing failure data for further in-depth examination.
- Maintenance pattern discovery: The system applies appropriate data mining algorithms to identify patterns, trends, and associations within the failure data. The system analyses the results of the data mining process to identify common failure patterns, root causes of failures, and relationships between different failure modes. These analysis contribute to understanding the underlying causes of failures and inform troubleshooting strategies.
- Contextualizing and visualizing in AR: The system visualizes the results of the data mining process to aid in interpretation and decision-making. In addition, the system contextualizes maintenance instructions and visualizes them in AR. These features enhance operator comprehension by overlaying relevant information onto the physical components of the rolling stock, providing a dynamic troubleshooting environment.
- Automated documenting: The AR system automates the documentation of data, reducing administrative tasks for operators. This automation ensures that data is organized systematically, contributing to sustainable relief from manual data management [258].

The AR visualization incorporates real-time data derived from rolling stock components, encompassing sensor data, diagnostic information, and historical performance metrics. The system renders this information in-situ through 3D visualization, aligning with the physical components of the rolling stock. Leveraging its spatial awareness capabilities for detecting and interpreting rolling stock components, the system determines the placements of in-situ 3D visualizations, overlaying virtual information logically within the AR environment.

8.5.2. UI experience requirements

The UI should be easy-to-use and easy to understand, even for users with varying levels of technical expertise. The maintenance guides presented in AR may involve many kinds of information signs, such as figures, colours, and graphs. The interaction with maintenance information is achieved by questioning and answering, selecting menus, scanning bar codes, object recognition, videos, pictures, and overlaying 3D objects [238]. Having a realistic representation of system components and contextual information enhances the understanding of information. To provide an engaging AR UI experience, the operator must be able to select, manipulate, control, edit, add, or delete 2D and 3D virtual objects in a real troubleshooting scenario [259][220]. Clear navigation and straightforward interactions are essential for efficient troubleshooting. Users may have different preferences for layout, display options, or the types of information presented, therefore, the UI should be customized to the user preference or specific troubleshooting scenario.

8.5.3. Operator input

The contribution of operator input lies in its emphasis on incorporating operator feedback and requirements throughout the development and evaluation process of the AR design guidelines. The quality and accuracy of the troubleshooting information presented in the AR UI are assessed by operators. Operator input supports further development of the AR design guidelines. The operator specifications include determining the level of expertise and troubleshooting habits and therefore require customized design with tailored-based information support [123]. Operator input on functional and UI experience requirements is collected while using the AR troubleshooting tool, including data accuracy, correctness and completeness, perceived usefulness and self-efficacy, and visibility, accessibility, and accuracy of 3D visualizations. Operator data is collected through workshops, interviews, observations, and usability testing.

8.6 Case study: troubleshooting rolling stock sanitary failure

This case study follows and seeks to gain contextual and in-depth knowledge about the development of AR design guidelines for troubleshooting rolling stock failures in a real industrial environment. The study reports on the initial, hand-over, and practice stages of the AR design guideline development. A qualitative field study research is employed to identify an appropriate rolling stock failure, utilize an iterative prototype development process, and reflect on troubleshooting functionality and UI experience through operator input.

8.6.1. Design considerations

The AR troubleshooting tool and design guidelines specifically target tasks related to the sanitary system failures of the refurbished double-decker rolling stock (VIRM-m1) [107]. The case study focuses on the functional and UI requirements of the AR design guidelines in the context of troubleshooting a sanitary system failure. In particular, the focus is on addressing issues related to the bioreactor pipe temperature being too low, a critical problem that impacts the functionality of the sanitary system. The operators utilizing the tool are 11 Dutch NS railway technicians specializing in sanitary troubleshooting and maintenance. The maintenance facility of NS serves as a testing location for the prototypes, where they are evaluated by the 11 experts. The evaluation metrics for evaluating the tool’s effectiveness include the accuracy of the process in identifying the root cause of the system issues, suggesting appropriate solutions, and gathering operator feedback on the tool’s usability, UI experience, and overall effectiveness in industrial scenarios.

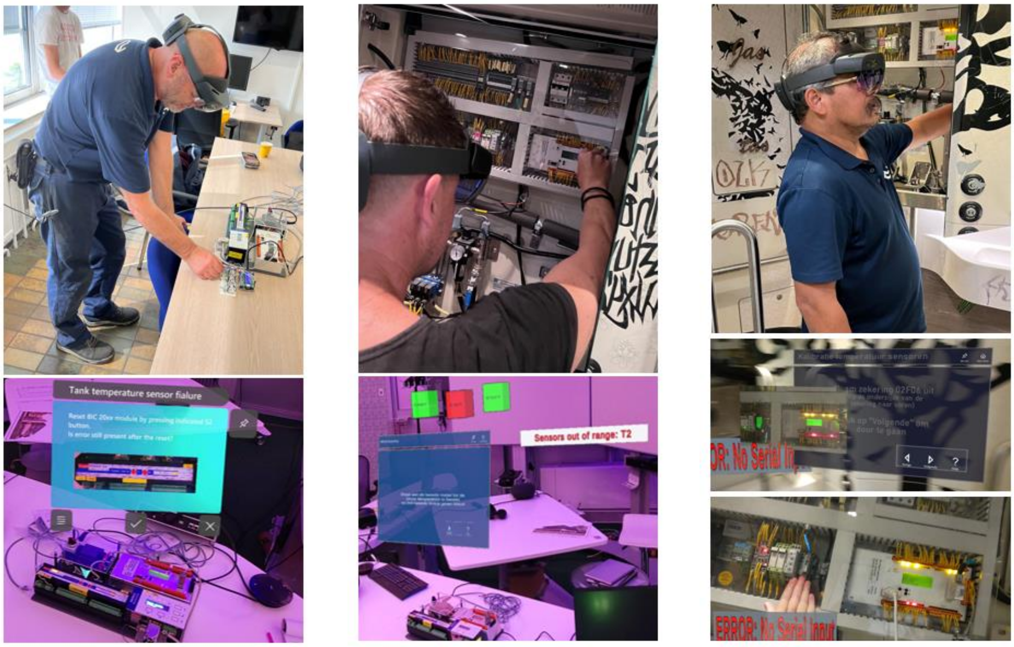
8.6.2. Rolling stock system failure specification

This case study examines the functional and UI requirements of the AR design guidelines for a troubleshooting support system for a sanitary system failure where the bioreactor pipe temperature is too low. The vacuum toilet consists of a toilet bowl with a water-level sensor, a water flushing system, an intermediate tank, a pinch valve, a valve block, and a control and signalling system [204]. The vacuum toilet components are controlled by the toilet PLC and ensure that after operating the flush button, the contents in the toilet are transported to the bioreactor. A bioreactor is a composite unit that biodegrades solids and sewage from the vacuum toilet and the sink [204]. The bioreactor provides separation of solids and water, filtration and neutralization of sewage by a bacterial colony, and neutralization of residual water by heating and discharging this on the railroad. Several studies show that the contamination of sensors and the hyalinization unit of the bioreactor is a major cause of malfunctions [204]. Debris accumulates around the heating element, causing the sensor to send false signals. A major problem in troubleshooting this sanitary failure is the lack of available data; over the past five years, data from only 133 maintenance actions have been documented. The current troubleshooting strategy consists of calibrating temperature sensors, resetting the toilet's PLC, performing a service flush, and inspecting physical wire connections. Information is extracted from various sources where the operator identifies the failure based on historical data, expertise, knowledge, and maintenance manuals. The current troubleshooting method is time-consuming because the operator has to consult all manuals and failure information sources, moreover, there is no standardized troubleshooting procedure. The proposed AR troubleshooting guidelines allow for more insightful troubleshooting by utilizing a centralized data platform, connecting real-time temperature data to the AR UI, finding the root cause of the problem by using FTA, FMEA, Root Cause Analysis (RCA), and case-based reasoning methods, and visualizing maintenance guides in 3D.

8.7 Iterative prototype development process

This work is based on an iterative prototyping process to explore the design space of the AR design guidelines by receiving intuitive and concise feedback from operators. Each prototype iteration builds upon the previous version, refining the AR troubleshooting tool to better meet operator needs and address real-world challenges. Feedback from operators drives continuous improvements, ensuring the effectiveness and usability of the final AR design guidelines.

The prototypes are built utilizing a 3D/AR Unity application on the HoloLens 2. Figure 8.4 presents the AR UI and the operators working with the troubleshooting prototypes. Designing an effective UI for AR troubleshooting involves considering various visual elements, e.g. icons, labels, and 3D models superimposed on the physical components, colour coding, e.g. faulty temperatures are red, correct temperatures are green, interactive elements, e.g. gesture commands or voice commands for handsfree use, and visual aids, e.g. videos and pictures of system components to supplement textual instructions.



(a) (b) (c)

Figure 8.4. AR UI and operators working with the troubleshooting prototypes (a) exploratory prototype, (b) experimental prototype, and (c) evolutionary prototype.

8.7.1. Exploratory prototype

The exploratory prototype simulates a simplified sanitary failure based on four sanitary components (toilet controller, bioreactor controller, temperature controllers, and BID bioreactor). It simulates temperature values of the bioreactor pipe temperature. Temperatures are set out of bounds to simulate a condensed troubleshooting scenario causing multiple system failures. The operator utilizes the AR troubleshooting prototype to solve the failure. The exploratory prototype receives feedback on UI clarity, including the brightness of backgrounds and fonts, prompting functional and UI design iterations.

<u>Feedback on the exploratory prototype:</u> All required maintenance and failure information was up-to-date for the condensed troubleshooting scenario. However, operators indicated that this troubleshooting scenario is unrealistic because of its compact setup. Operator input on a minimalistic design AR UI heuristic reveals that the background of the maintenance manuals and fonts were too bright, and the cursor and screen were blurry. The exploratory prototype requires functional and UI design iterations by simulating a real failure in the rolling stock.

Prototype improvements: Creating a realistic troubleshooting scenario, leading to functional and UI design iterations.

8.7.2. Experimental prototype

The experimental prototype iterates upon the exploratory prototype, providing more comprehensive instructions, 3D directions, and real-time data support. This prototype emphasizes examining whether the provided information is correct and accurate, simulates real-time temperature data, and presents the maintenance activities accordingly. The FTA of the failure is comprehended and includes calibration of temperature sensors. The background and font colour require darkening, additional 3D visualizations are presented in the same way as in the exploratory prototype. The HoloLens 2 is calibrated for each operator individually.

Feedback on the experimental prototype: According to the operators, the information presented was accurate, up-to-date, clearly presented, and consistent with existing work descriptions. Operators were reluctant to simulate a single system failure because, in real troubleshooting scenarios, multiple failures simultaneously occur. In addition, the troubleshooting scenario requires a more realistic simulation by calibrating and resetting temperature sensors by connecting a service computer to the rolling stock system. The 3D visualizations are considered useful for operators, especially by pointing out system components and linking maintenance activities to them.

Prototype improvements: Focus should be put on a realistic sensor calibration.

8.7.3. Evolutionary prototype

The evolutionary prototype simulates an actual sanitary troubleshooting scenario on rolling stock, incorporating operator feedback from previous versions. An actual sanitary troubleshooting scenario is simulated on the rolling stock by having the operator reset and calibrate temperature sensors using a service computer. Visual aids (e.g. pictures of components) supplement the available AR maintenance manuals. It excels in providing accurate and up-to-date information in a real troubleshooting context.

Feedback on the evolutionary prototype: The operators were enthusiastic about the evolutionary prototype, because all data was up-to-date and accurate, clearly presented, and embedded in a real troubleshooting scenario. The operators performed the troubleshooting task well, including calibrating temperature sensors as indicated in the AR instructions. The operators were most enthusiastic about the 3D visualization and step-by-step guidance of real-time maintenance instructions. Some operators see the added value of capturing maintenance tasks and recording the execution time. This information is useful for future decision-making and maintenance planning. Not all operators agreed because managers can blame operators for making mistakes and track how long operators take to complete tasks.

Prototype improvements: Additional features of tracking maintenance activities and documenting data automatically

8.7.4. Prototype improvements

Table 8.5 presents all key functionalities, UI design heuristics, and operator requirements for each prototype. Following each evaluation, iterations are implemented based on feedback regarding functional and UI experience requirements, as well as operator needs. Common themes, suggestions, key insights, and areas for improvements highlighted by operators are identified and prioritized based on their importance and potential impact on improving the AR system. The table documents new additions to each requirement in the prototype column. A two-week interval between iterations allows researchers sufficient time to analyse feedback and implement changes. To validate the new iterations, operators are asked the same set of questions.

Table 8.5. Functional requirements, UI design heuristics, and operator requirements of all prototypes.

Prototype	**Exploratory prototype**	**Experimental prototype**	**Evolutionary prototype**
Functional requirements	• Providing complete work instructions by combining new FTA, RCA, FMEA, and case-based reasoning with existing maintenance manuals. • Offering real-time pipe temperature data • Generate visualizations of four sanitary components to superimpose 3D models and align them on real objects • Providing handsfree use	• Extending FTA and information supply • Real-time data extraction from rolling stock exploration • Create correct and accurate maintenance information • Contextualizing real troubleshooting scenarios	• Incorporating real troubleshooting scenarios • Tracking and documenting maintenance activities
UI experience requirements	• Structuring and organizing UI elements • Alignment 3D overlay with real object	• Customize the background and colour schemes of maintenance manuals based on operator needs	• Complementary visual aids (videos, pictures)

Prototype	Exploratory prototype	Experimental prototype	Evolutionary prototype
	• Adequate visibility, contrast, and font size of visuals • Simple maintenance instructions; minimizing task performance	• Adding 3D visualizations based on work instructions • Eye calibration tailored to AR device	
Operator requirements	• Provide user-friendly and easy-to-use hardware and software systems • Simplify the troubleshooting scenario to understand the basic concept	• Avoid dangerous situations (hardware may reduce visibility) • Reduce physical efforts • Simulate real-life troubleshooting scenarios	• Maintenance support tailored to the operator's expertise and knowledge • Incorporate environmental conditions (operator's location leads to hardware limitations) • Reduce administrative tasks

8.7.5. Qualitative field study results

The qualitative study and prototype development process aimed to contribute valuable insights to the existing knowledge base outlined in Table 8.2. The initial phase of the qualitative field study involved conducting semi-structured interviews to explore participant's familiarity and experience with AR, their existing troubleshooting strategies, and the associated requirements. Discussions encompassed both current and potential applications of AR, delving into its advantages and disadvantages. Among the participants, only one operator engaged with Virtual Reality (VR) to simulate a door system failure for educational purposes. Several operators faced challenges in conceptualizing AR as part of troubleshooting procedures, primarily influenced by social factors. Concerns included the perceived impact of automation on systematic thinking, the increased physical burden of maintenance tasks, and apprehension about potential job displacement by robots. One operator explicitly expressed job security concerns, stating, "My job is at risk ". However, the majority of the participants recognized the value of AR in providing immediate, precise directions and offering an overview of system failures, thereby enhancing the troubleshooting process for rolling stock issues. An optimistic perspective was shared by an operator who envisioned significant potential in AR troubleshooting, stating, "I see a great potential in AR troubleshooting and support future developments. Especially real-time step-by-step guidance will help me in my work". The interview quotes are categorized into different themes, Table 8.6 represents examples of how quotes were categorised in themes.

Table 8.6. Quote and theme division.

Prototype evaluation	Question	Response	Theme
Exploratory prototype	What kind of visualizations will support you better in the current troubleshooting prototype?	The draft is fine, just enough to complete the tasks.	Visualizing components and maintenance tasks in 3D
Experimental prototype	What is your opinion on the timing and location of the 3D visualizations?	Have to get used to pressing the buttons accurately and eyes have to adjust to the HoloLens 2 (the participant is wearing glasses).	Gesture interaction
Evolutionary prototype	What is your opinion on the AR troubleshooting method?	Clear and positive, especially when using this method for complex rolling stock failures. In terms of safety, you need to be aware of your situation. The HoloLens device is sizable, and caution is advised to avoid navigating into confined or expansive areas.	Problem-solving strategy Situational awareness

The primary outcomes of the qualitative field study results are detailed in Table 8.7. During prototype testing, operators consistently emphasized the importance of a clean and simple AR UI design. This allows them to quickly grasp essential information without cognitive overload.

Table 8.7. Semi-structured interview results.

Operator reflections on AR UI	Operator reflections on functionality	Operator reflections
• Text, figures, and supplementary information should be tailored to the eyesight and preferences of the operator • Virtual dashboard supports understanding of visualizations • Visualizing components and maintenance tasks in 3D are understandable and	• All information is up-to-date and aligned with maintenance standards • Problem-solving strategy is convenient and efficient • Automatic recording of maintenance information supports future maintenance planning and scheduling	• Ergonomics (operators wearing glasses, temperature-dependent working conditions) • Situational awareness (potentially dangerous working conditions) • A real-life troubleshooting scenario use case is key for testing the application

Operator reflections on AR UI	Operator reflections on functionality	Operator reflections
increase the usefulness of the tool • Gestures to interact with the virtual objects are easy to follow • Virtual alignment with reality is not configured properly and high response time	• Understanding and identifying the problem is being supported • Not possible to give direct operator input to the system • No activity tracking is available	• Existing knowledge and expertise is complemented by the tool • Handsfree working while having maintenance support

8.8 AR design guidelines

Translating results from prototype feedback to design guidelines involves extracting insights gained from operator evaluations on the iterative prototypes and incorporating them into actionable recommendations. The prioritized recommendations are organized into a set of guidelines that address specific feedback or observed issues from the prototypes.

The identified functional limitations addressed by operators include (1) information loss due to incorrect and incomplete documentation of maintenance actions, (2) lack of access to failure and historical data of the rolling stock, (3) inefficient problem-solving strategies, (4) incomplete work descriptions, and (5) insufficient expert knowledge due to the complex nature of rolling stock system failures. The qualitative field study and prototype development process underscore the necessity of a centralized platform to organize maintenance data, coupled with intuitive 3D visualizations, to provide operators with accurate work descriptions, minimizing cognitive loads. The success of UI experience in decision-making procedures relies on well-constructed contextual 3D visualizations, emphasizing on the operator's knowledge, expertise level, and personal preferences in determining customized troubleshooting functionalities. The presented AR guidelines representing functional and UI experience requirements are set and influenced by expert troubleshooting operators; The results are set into the following design guidelines.

1. Centralize the AR UI system: Establish a centralized data platform that seamlessly integrates online and offline maintenance and rolling stock failure data. Ensure that the AR UI conveys only essential information for understanding system failure behaviour. Combine maintenance manuals and procedures with real-time operational rolling stock data and fault-diagnosing algorithms. Implement automatic maintenance activity tracking and storing for sustainable relief.
2. Provide a problem-solving strategy: Develop an information processing and prognostic approach. Design user-friendly and clear 3D visualizations of rolling stock components, enabling navigation and interaction. Employ familiar design elements to improve usability. Superimposing system

information, utilizing colour coding, labels, and annotations to emphasize critical details and facilitate step-by-step guidance. Ensure the visualizations effectively showcase failure and maintenance patterns.

3. Use a minimalistic design for AR UI: Opt for a minimalist design in the AR UI to prevent mental overload and minimize distractions. This involves simplifying the interface by removing unnecessary elements, reducing clutter, and focusing on essential information. Implement clean and simple navigation menus and prioritize clarity and readability in text and graphics. Align superimposed 3D visualization with the physical object, providing simple yet effective maintenance instructions with complementary video and graphics. Develop a customized tool that caters to the preferences and visual capabilities of each operator.
4. Ensure efficient information transfer: Ensure efficient information transfer by optimizing data processing algorithms to handle real-time data streams and combine them with existing manuals. Implement mechanisms for prioritizing crucial information related to troubleshooting scenarios, ensuring that operators receive timely and relevant data. Additionally, consider general factors such as maintenance instruction visibility under different ambient lighting conditions, minimizing physical distractions, and robust connectivity to address potential internet connection issues.
5. Use operator experience and knowledge for AR troubleshooting: Engage operators with diverse experiences and knowledge levels throughout the AR design process. Conduct real-life troubleshooting scenarios to contextualize environmental conditions, ensuring a human-centred design approach.
6. Identify a clear industrial application: Prioritize a clear industrial application by defining specific use cases that highlight the relative advantage of the AR troubleshooting tool. Conduct user perception studies to validate its effectiveness across different industrial contexts.

8.9 Discussion

Understanding and acknowledging the limitations of the guidelines will help refine their relevance and applicability across a range of scenarios within the context of AR troubleshooting for rolling stock system failures. Ongoing evaluation and feedback loops with operators and industry stakeholders can also contribute to refining and updating the guidelines as technology and operational practices evolve. If the tool introduces cognitive overload, discomfort, or other human-centric issues, it could impact its usability and the guidelines' applicability. If data is incomplete, inaccurate, or unavailable, it may impact the tool's functionality and the guidelines' relevance. Software and hardware capabilities can lack features or advancements required for troubleshooting, therefore, the guidelines may need adjustments to align with the available technology. In addition, factors such as lighting, weather, and the physical layout of the workspace can impact the tool's performance. The guidelines require validity in diverse contexts, e.g. different maintenance scenarios, different types of rolling stock, and scalability to larger systems.

The main advantages of the troubleshooting tool perceived by operators are: (1) having hands-free maintenance support, (2) having access to all relevant real-time information, and (3) receiving user-friendly and clear 3D visualizations pointing out rolling stock components. A disadvantage of the current tool is the lack of receiving feedback, e.g. the AR maintenance instructions cannot track the physical maintenance activities automatically. Moreover, no real-time connection to the rolling stock is possible; a direct rolling stock troubleshooting connection is essential to provide immediate feedback to the operator when troubleshooting complex failures.

8.10 Conclusions and recommendations

This research examines the development process of holistic design guidelines to create an AR troubleshooting tool for rolling stock system failures. The research findings contribute novel insights and approaches to the field of AR applications in troubleshooting scenarios. A qualitative field study was conducted involving 11 participants, with each participant being a sanitary troubleshooting expert. The results show that operators can more easily solve complex rolling stock system failures by using AR. This study places a strong emphasis on tailoring AR UI elements and functionalities to suit the specific needs and preferences of operators. This tailored approach ensures that the AR system aligns seamlessly with the operator's visual and cognitive requirements. Unlike many existing studies, this research emphasizes the significance of real-life testing in troubleshooting scenarios. The iterative prototyping process involves simulated real failures in rolling stock systems, allowing operators to interact with the AR tool in scenarios closely resembling actual maintenance tasks.

In conclusion, the process of translating prototype feedback into design guidelines for AR troubleshooting is an iterative process driven by insights gleaned from operator evaluations. These guidelines aim to address specific feedback and observed limitations identified during the prototype testing phase. Through the iterative development process, functional limitations highlighted by operators, such as information loss, inefficient problem-solving strategies, and insufficient access to expert knowledge, have been identified and addressed. The qualitative field study underscores the importance of a centralized data platform for organizing maintenance data and intuitive 3D visualizations to minimize cognitive loads. The success of the guidelines relies on well-constructed contextual 3D visualizations that cater to the operator's knowledge, expertise, and preferences. By adhering to the presented AR design guidelines, which emphasize a centralized data platform, problem-solving strategies, minimalist UI design, efficient information transfer, leveraging operator experience, and identifying clear industrial applications, AR troubleshooting tools can better meet the needs of operators and enhance the maintenance process in real-world scenarios across various industrial contexts.

To incorporate the design guidelines into maintenance manuals and standards, a structured approach is essential to ensure seamless integration and adoption by maintenance personnel. Sections should be identified in existing maintenance manuals where the design guidelines can be incorporated. Revision of the maintenance procedures requires alignment with the design guidelines, including recommended problem-solving strategies, UI elements, and information transfer mechanisms. Training materials to educate maintenance personnel on the revised procedures and the use of AR troubleshooting tools are required. The AR troubleshooting tool should be integrated into existing maintenance procedures and company databases to maximize effectiveness. Seamless data exchange and integration enhance the tool's capabilities and provide operators with comprehensive real-time information. Extensive training and familiarization sessions ensure a smooth transition for using the AR troubleshooting tool help operators understand the full potential of the application, and encourage its use. Continuous improvements by monitoring the effectiveness of the design guidelines in practice require a process of gathering operator feedback to identify areas for further refinement and enhancement.

This research adopts a comprehensive approach that integrates various facets including UI design, functionality real-life testing, data integration, and operator customization, making it a valuable addition to the field of AR applications in industrial maintenance. By formulating these design guidelines for an AR troubleshooting tool, this study serves as a foundational resource for researchers seeking to enhance the usability of AR systems by prioritising human factors.

Chapter 9 – An augmented reality roadmap for rolling stock organizations

Publication history: Thesis chapter

9.1 Theme V: Organizational impact

This chapter outlines the implementation of AR in rolling stock organizations through the development of a roadmap (Figure 9.1). By offering valuable guidance, it contributes to assisting rolling stock organizations in integrating AR solutions within the intricate landscape of railway operations and maintenance.

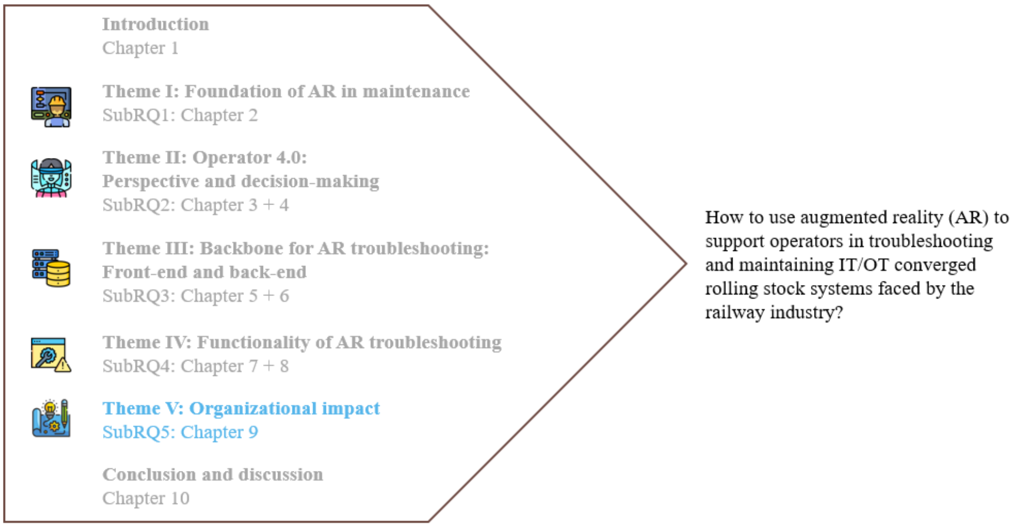


Figure 9.1. Theme V: Organizational impact.

Organizations anticipate significant challenges regarding implementing AR within their supply chains, operations, and overall business models. The growing complexity across all levels of organizations has led to uncertainty about both technological and organizational capabilities, and the most suitable strategies for adopting AR. While concerns about understanding AR persist, there is currently a lack of well-defined organizational capabilities and methodologies to shape the vision of AR within organizations. In this chapter, a maturity model grounded in empirical research is combined with ISM and a technology-focused AR roadmap. This approach is tailored for interpreting the AR readiness of industrial organizations, particularly in the rolling stock maintenance domain, and charting a strategic path for the future. The maturity model used in this study encompasses eight key dimensions and includes 39 maturity items. It has been validated and verified through applications in a rolling stock organization, reinforcing insights gained from this AR roadmap. The results indicate that the organization falls into the moderate maturity level, with a maturity score of 2.9, and the highest attainable maturity score being 5. Additionally, a case study exemplifies the validity of the AR roadmap in a real-world setting, demonstrating its functionality and adaptability.

9.2 Introduction

AR is a key technology for Industry 4.0 concepts and is one of the main technologies to drive the development of such concepts in the industry according to the European Union [260]. Although academic research on AR is growing exponentially, evidence of AR implementation in practice is still scarce. Moreover, the challenges organizations face when implementing AR seem to be even less addressed [165]. Research on the long-term effectiveness and impact of AR on organizations is limited. The organizational context relates to the characteristics and resources made available to an organization itself and depends on the company culture regarding the adoption of new technologies (chapter 2) [261]; (top) management support has a dominant role in promoting innovation [262]. The organization needs to be prepared and ready for AR implementation (chapter 7), maintenance processes need to be adapted (chapter 4), maintenance operators need to be involved and trained (chapter 3 and 8), and the technology has to be integrated into existing IT infrastructures (chapter 5 and 6) [165]. There is a gap in understanding how AR solutions integrate with existing organizational systems while seamless integration is crucial for practical implementation. To gain a deeper insight into this integration, assessing the current state of AR implementation within an organization is essential. Maturity models and readiness assessments play a vital role in this evaluation. Organizations seeking innovative maintenance strategies are encouraged to foster innovations through interdepartmental collaboration, outlining clear solutions with defined goals. In addressing these needs, this study introduces an AR roadmap designed to steer organizations from their current situation toward the effective utilization of AR in rolling stock maintenance operations.

The maturity model and readiness assessment can help support rolling stock organizations to evaluate their current state in terms of AR adoption, including assessing existing processes, technology infrastructure, operator skills, and overall organizational readiness for AR implementation. In the landscape of existing structural models, such as System Dynamics (SD), Analytical Hierarchy Process (AHP), Fuzzy Cognitive Maps (FCM), Bayesian Belief Networks (BBN), Graph Theory Models (GTM), and ISM, ISM with its focus on interpretability and understanding structured relationships, is favoured when developing strategic roadmaps for technologies like AR. In the context of AR implementation, ISM supports understanding the relationships between different aspects of the organization that influence the introduction of AR in maintenance operations, including organizational culture, technology infrastructure, interdepartmental collaborations, and strategic goals [263]. Maturity models provide a structured approach for assessing the readiness of AR technology implementation in organizations, while ISM helps understand the intricate relationships between different aspects of the organization. ISM assists in prioritizing elements identified in the maturity assessment. Combining the two methods contributes to the development of a well-informed AR roadmap for rolling stock organizations to effectively incorporate AR into their maintenance operations.

The core objective of this study involves developing an roadmap that explains the order in which requirement of AR in rolling stock maintenance should be developed and leveraged. First, the study conducts a content-centric review of the extant literature and identifies approaches that have been reported on maturity and readiness assessments. Second, the study leverages the ISM technique and expert's opinions to identify the sequential relationships among the enablers identified and develop an interpretive roadmap. Third, the study relies on expert judgment in a case study to interpret the contextual relationships identified.

9.3 Methodology

This research adopts Becker's step-by-step process to perform a maturity and readiness assessment and develop an AR roadmap. It is strongly based on Hevner's design science approach by offering a rigorous methodology [264]. Figure 9.2 presents the study design proposal.

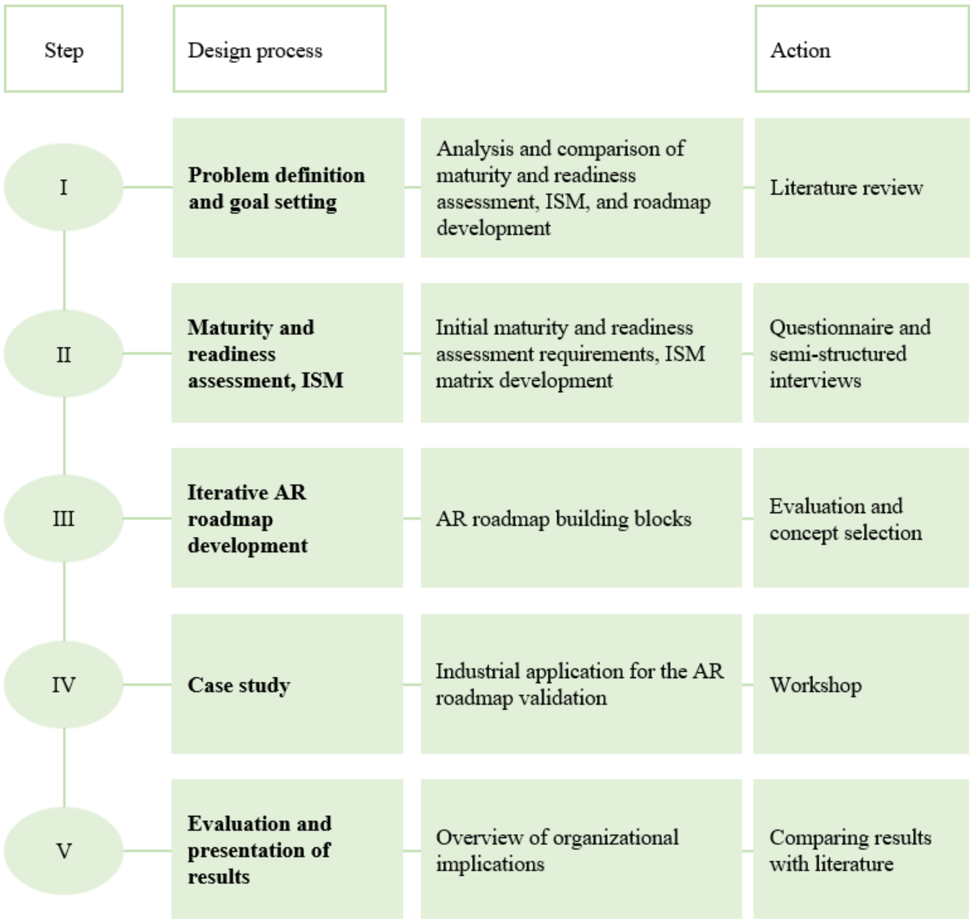


Figure 9.2. Study design proposal, adapted from [264].

9.3.1. Study design proposal: Step I & Step II

The first step of the study design proposal is conducting a literature review of existing readiness and maturity models, ISM, and the requirements for an AR roadmap, forming the foundation for this research.

In the subsequent step, illustrated as Step II in Figure 9.2, the readiness and maturity analysis's dimensions, measurement items, and levels of maturity, along with their relevant characteristics, are established. To perform a pairwise comparison of maturity items and dimensions, 11 NS experts specializing in innovations, management, and maintenance in the railway industry were selected and interviewed. These experts are actively engaged in AR projects for rolling stock operations and have an average experience of 10 years in their respective fields, ensuring a diverse and well-balanced participants group.

The research employs questionnaires and semi-structured interviews to gather insights from these experts for the maturity and readiness assessment. Given the potential subjectivity of participants' opinions, the support of semi-structured interviews becomes crucial. Both the questionnaire and semi-structured interview will provide insights into the current status of AR applications within a rolling stock organization by providing data input for the maturity and readiness assessment as well as ISM. Additionally, the results offer valuable information regarding the essential building blocks for constructing an AR roadmap. The evaluation of the maturity involves a standardized questionnaire consisting of one closed-ended question per item. The online questionnaire takes approximately 10 minutes, whereas the semi-structured interview takes about 60-90 minutes.

The online questionnaire, comprising 31 questions, is distributed to the 11 AR, maintenance, and innovation experts. The five-point Likert scale is adopted to record the responses for each maturity item in the questionnaire. Here, '1' represents complete disagreement with the statement, whereas '5' represents complete agreement from the participant. The organizational maturity score is calculated through structured closed-end questions for each maturity item separately. To support the questionnaire results and avoid bias, a semi-structured interview is conducted. This interview elaborates on the online questionnaire by questioning participants and gaining detailed information on maturity items. The questionnaire and the semi-structured interview are presented in Appendix I. After the semi-structured interviews, the answers are processed in ATLAS.ti [45], coded and categorized into the different maturity items to support the online questionnaire results.

After receiving the responses to the online questionnaire, the Likert-scale results are processed in a software-supported manner and the maturity scores are automatically calculated and summarized in a compact maturity report. Afterwards, calculated points of maturity dimensions are grouped to identify the maturity levels individually and overall. The weighting factor for calculating the overall maturity score is assumed to be equally distributed as 1 to not influence the study with preset weighting factors.

Therefore, the overall maturity score of each dimensions results from calculating the weighted average of all measurement items within its related maturity dimension.

9.3.2. Study design proposal: Step III

The iterative AR roadmap development procedure (Step III, Figure 9.2) includes three distinct phases: (1) the initial phase to create a complete understanding of the AR domain, (2) the development phase to design the AR roadmap using a maturity and readiness assessment, and (3) the validating phase to test the results in a real-life application. The results from the readiness and maturity assessment are requirements for the AR roadmap. ISM supports determining the relevant characteristics of the AR roadmap for rolling stock organizations by determining the sequence and purpose of complex relationships between elements in the roadmap.

9.3.3. Study design proposal: Step IV & Step V

A case study approach is adopted in a workshop session to recognize and confirm the AR roadmap for rolling stock organizations (Step IV, Figure 9.2). The AR roadmap is finally tested in an industrial setting and feedback from 5 experts is sought for its practicability. These experts represent a subset of the larger group of 11 experts initially engaged in the study and are actively involved in an AR rolling stock maintenance project. A real-life case study simulates a rolling stock system failure and provides insight into the AR requirements that organizations should adopt from both technological and business perspectives. These insights will support the further development of the AR organizational roadmap. The online workshop, focussing on the practical application of the AR roadmap in a real-life case study, takes approximately 60 minutes. Based on the response from the practitioners and users of the AR roadmap, changes can be incorporated (Step V, Figure 9.2).

9.4 Step I & Step II: "Problem definition and goal setting" & "Maturity and readiness assessment, ISM"

Maturity models rapidly develop in dynamic environments of business, including universal models as well as models strictly dedicated to a particular business and a particular scope of improvement [265][266]. For each business area in organizations, a way of maturity assessment can be developed, e.g. IT management [264], optimization of processes [264], and agility of organizations [267]. Roadmaps for AI-related technologies, managing data, and realizing smart manufacturing have been analysed, however, there is no single roadmap for AR adoption in rolling stock organizations [266].

9.4.1. AR maturity and readiness assessment model

This study seeks insights from maturity models in related Industry 4.0 domains and tailors the focus to enhance applicability within the AR rolling stock context. Related work focused on Industry 4.0 maturity levels and used 9 dimensions and 62 maturity items to assess the organization's maturity level [268]. However, these models are not technology and maintenance domain-specific, the maturity model must correspond with the business models that exist in particular economies [269]. Therefore, this work adopts 7 dimensions and replaces the dimensions 'customers' and 'products' with 'maintenance operations' to fit in the rolling stock maintenance domain. The proposed AR readiness and maturity assessment for rolling stock organizations includes 36 maturity measurement items spread across 8 dimensions. The prime focus is 'strategy', 'leadership', 'maintenance operations', 'general operations', 'culture', 'people', 'governance', and 'technology'.

The measurement items are derived from previous studies on readiness and maturity models in the Industry 4.0, innovations, and maintenance domain [270][271]. The maturity items are selected on industry scope, thus creating a chance to obtain data from AR technology in the maintenance domain, measure the organization's functional operations, and shape the business strategy and organization [268][272]. The maturity and readiness assessment aims to have an in-depth assessment rather than a basic formulation for assessment which is common in existing maturity models. Table 9.1 presents the organizational dimensions involved in the maturity model together with explanatory items to support understanding.

Table 9.1. AR measurement items for each maturity dimension.

Dimension	**Measurement items**	**Detailing of the measurement items**
(1) Strategy	Digital vision and roadmap	Concise vision and roadmap for the future
	Resources	Available resources for AR realization, pre-stated level of investments for AR transformations
	Communication and documentation	Knowledge-sharing and documentation on open innovation, enabling cross-company collaboration opportunities
	Business model	Capability to modify the existing business model suitable for AR
(2) Culture	Cross company collaboration	Creating a work environment giving employees space for open and honest communication for trust-filled relationships
	Knowledge management	Organizing, creating, using, and sharing the knowledge and information in the organization
	Value of IT	Aligning IT strategy with its business goals to generate new AR-based operations
	Company culture	Enable a continuous improvement culture to adopt AR alignment
	Openness to innovation	Ensure a clear and concise innovation vision and company culture keeping focus on the organization's long- and short-term goals
	Ambition	Relate ambition to organizational commitment beyond achievement striving
	Inclusion	Consider using surveys to collect employees' feedback on determine employees inclusion in technology adoption, discuss areas for improvement
(3) Governance	Intellectual property	Managing and protecting intellectual property of the technology

Dimension	Measurement items	Detailing of the measurement items
	Information management	Ability to manage the organization's content and ensure company data and AR devices are stored and managed securely while maintaining compliance
	Innovation programs	Starting pilot programs for AR-based trials related to functionality, hardware, and management
	Safety standards	Setting procedures, policies, rules, and regulations affecting safety measurements
	Data security	Securing the organization's data and operator's personal information while optimizing AR-based maintenance support
	Technology standards	Establishment of rules and regulations for using AR technologies
	Adaptability of standards	Capable of adjusting the organization process and procedures for new AR technology standards
(4) Maintenance operations	Maintenance information	The organization's level of automatic fault-diagnosis capabilities by utilization of real-time maintenance data, digitization of maintenance manuals, procedures, etc.
	Digital documentation	Support maintenance operations by enabling rolling stock monitoring and control, the obtained data uses what-if analysis to build futuristic scenarios for decision support
	Operator integration	The operator gives input to the AR system and embeds AR into his work procedures
	Operator's skills	Operator's digital skills and qualifications to adopt AR, experience with AR technologies for work assistance by visualizing objects
(5) Technology	Hard/software	Existence of digitized IT, utilization of HMD or mobile devices
	Cloud computing	Streamlining maintenance efficiency with online computing applications, implementing business software and algorithms to simplify maintenance and general operations
	Sensor data	Processing sensor data by utilizing AI-based cognitive technologies like NLP, Speech recognition, Rule-based systems, etc.
	Digital platform	Provide a digital platform for operators to know the maintenance status of the rolling stock
(6) People	Openness to change	Ability to integrate operator needs and/or preferences in the AR development process
	Idea generation	Creating, developing, and communicating abstract, concrete or visual AR applications. Capable of identifying complex organizational struggles and potential AR solutions
	Interdisciplinary work	The existence of dedicated teams in the company to drive AR across the organization
	IT competence	Increasing employee efficiency by supporting complex maintenance tasks, eliminating administrative work, and repetitive tasks, and documenting knowledge
	Flexibilization of work	Flexible work conditions allow the employees to incorporate AR technologies
(7) Leadership	Central coordination	Supporting management and leadership toward AR transformation activities

Dimension	Measurement items	Detailing of the measurement items
	Competence	Leadership skills and behaviour that contribute to superior performance
	Willingness	Willingness to lead and manage AR projects
(8) General operations	Adaptability of processes	Vision on AR product and process development and implementation phase
	Digitization of processes	Enabling sharing data and recognizing patterns in large amounts of operational information
	Standardization of processes	Ability to use AR for standardized work, incorporate AR in the standardized business structure
	Stakeholder integration	Establish positive collaborative relationships with a wide variety of stakeholders
	Interdepartmental collaborations	Achieving a common goal by collaborating with multi-departmental experts

9.4.2. Interpretive structural modelling for AR road mapping

Various approaches have been employed to assess the advantages of innovative systems. ISM stands out as a well-established method in the context of adopting innovative systems by adding value in examining the dynamics of complex systems [273]. ISM is suitable and beneficial for research in study areas in which limited experts are available and, hence, appropriate for AR in rolling stock maintenance adoption. As highlighted in [274], the reliability of ISM depends on expert experience and in-depth feedback. Therefore, this study employs a qualitative three-stage methodology outlined by [275]:

- Stage 1: Identifying the benefits of AR in rolling stock maintenance
- Stage 2: Feedback from experts on benefits to check the validity, clarity, and representativeness,
- Stage 3: Establishing a hierarchical level of factors

Appendix II provides an elaborate description of the three-stage methodology employed. Figure 9.3 illustrates the hierarchical structure of the maturity dimensions derived from the three-stage methodology.

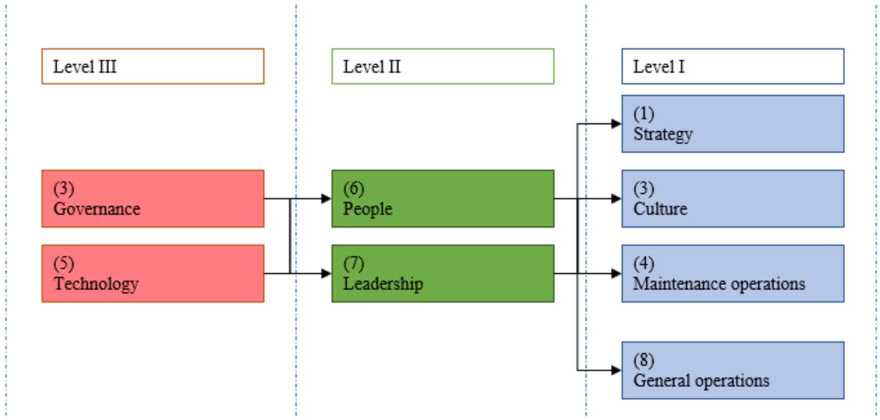


Figure 9.3. Hierarchical structure of maturity dimensions.

9.5 Step III: "Iterative AR roadmap development"

In the context of railway maintenance, technology, and future visions, an AR roadmap outlines a detailed plan involving developing and implementing an AR solution and is essential for communication among team members, stakeholders, and decision-makers involved in an AR project. The measurement items and dimensions from maturity and readiness assessments can be integrated into the development of the AR roadmap by aligning them with the key aspects of the roadmap requirements [276][277][278]:

1. Objectives and goals to scope down the project (chapter 2). Align the objectives and goals with dimensions such as 'strategy', 'leadership', and 'technology' from the maturity model.
2. Use case identification to identify where AR can bring value (chapter 2). Utilize the readiness assessment to identify organizational strengths and weaknesses, helping prioritize use cases based on the organization's readiness. Dimensions like 'maintenance operations', 'general operations', and 'technology' could influence the use case identification.
3. Technology requirements such as programming language, frameworks, hardware/software requirements (chapter 6 and chapter 7). Link technology requirements to the 'technology' dimension of the maturity model. Measurement items can cover technological capabilities, infrastructure readiness, and compliance with industry standards.
4. Data integration to incorporate AR in existing IT structures (chapter 5 and chapter 6). Align with 'technology' and 'governance' dimensions in the maturity model. Measurement items focus on data management, integration capabilities, and adherence to data governance.
5. Functionality description for content creation including the user experience and interface (chapter 7 and 8). Corresponds to various dimensions such as 'technology', 'culture', and 'people'. The measurement items include usability, user experience, training requirements, and cultural acceptance of new technologies.

6. Organizational requirements reflecting on regulatory compliance and security measures and human-AR interaction (chapter 3 and 4). Relates to dimensions like ‘leadership’, ‘strategy’, ‘culture’, and ‘governance’ in the maturity model. The measurement items encompass regulatory compliance, security measurements, and change management readiness.

The proposed roadmap structure was designed to be readable for non-AR experts to understand what the main requirements are to implement or to outsource an AR-based maintenance solution. The AR roadmap is presented to provide a structured approach to achieving project objectives and is illustrated in Figure 9.4. The elements within the AR roadmap are constructed based on insights from earlier thesis chapters, incorporating measurement items from Table 9.1. The input for the AR journey is drawn from chapters 2 and 7, operational tasks are informed by content in chapters 3 and 4, information supply is gleaned from chapters 5 and 6, AR technology is rooted in chapters 7 and 8, whereas the operational requirements are derived from the specified measurement items. The proposed method can support the selection of AR in different maintenance scenarios because it must consider the specific characteristics, requirements, and specifications of each scenario.

The user profiles define the basic type of user who will interact and be responsible for each task of the AR roadmap and are: operators, technical managers, IT experts, OT experts, AR experts, quality experts, AI experts, and maintenance experts. This task division is not mandatory because each organization has its hierarchy, job assignment, and responsibilities. Organizations will have to choose if the proposed task division is compatible with their corporate requirement, otherwise, adaption or outsourcing is required.

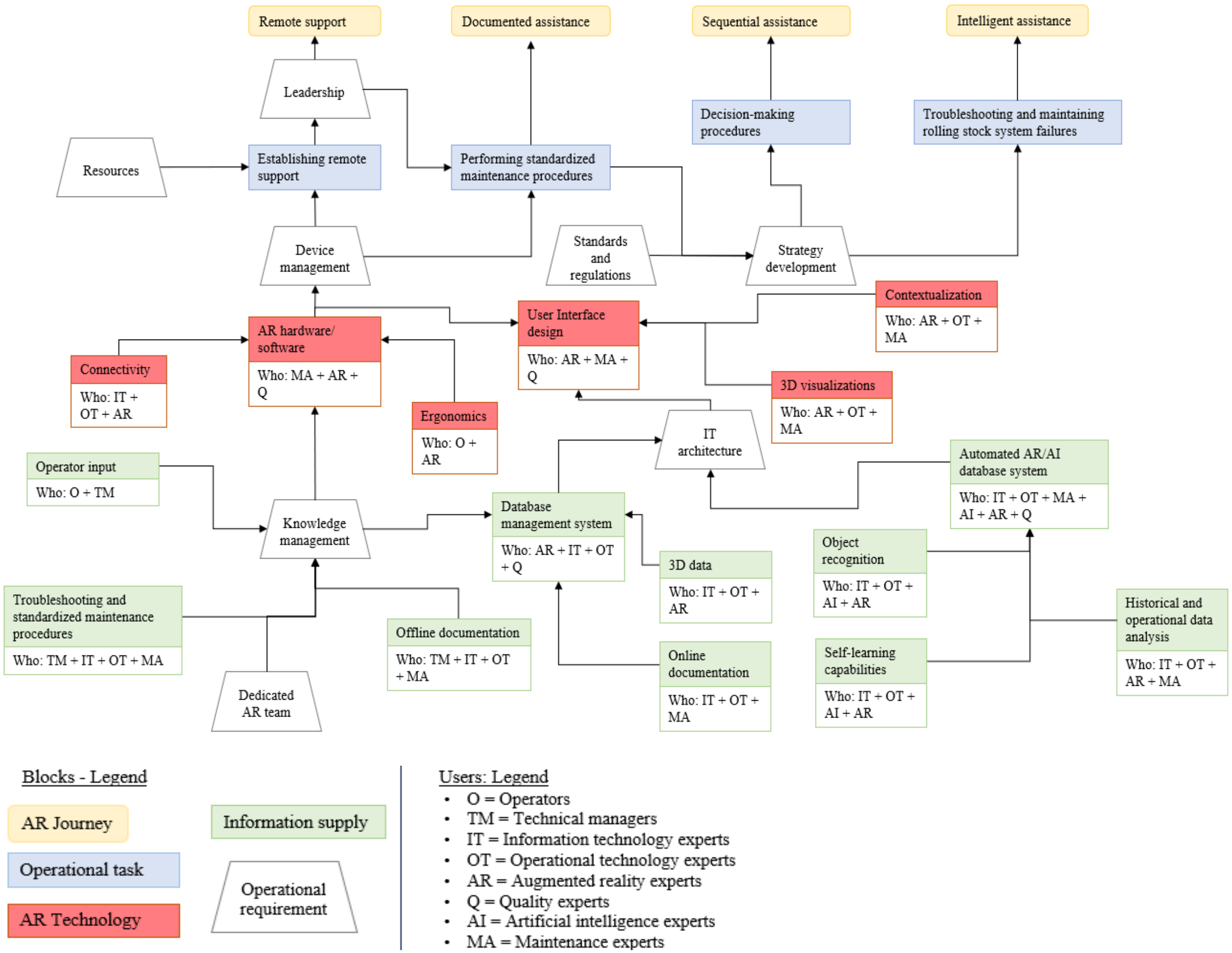


Figure 9.4. AR roadmap for rolling stock organizations.

9.5.1. *AR journey*

Four distinct goals are formulated regarding AR for rolling stock maintenance: (i) remote support, e.g. providing assistance and guidance to operators in remote locations [223] (ii) documented assistance, e.g. providing visual step-by-step guidance based on traditional written or video maintenance instructions [279] (iii) sequential assistance, e.g. guiding through a series of steps, procedures, or tasks in logic and sequential order by overlaying 3D visualizations and markers in the operator's field of view [59], and (iv) intelligent assistance, e.g. integrating AI and ML capabilities into AR applications to enhance the system in understanding, adapting, and responding to the operator interactions and environment [280]. All these individual goals have been grouped, based on existing literature and on previous thesis chapters, and contribute to building an AR portfolio related to rolling stock maintenance as the goals build upon each other.

9.5.2. *Operational task*

The evolution of manufacturing, maintenance, and digitized systems underscores the pivotal role that human capabilities will play in advancing decision-making and will use hybrid AR/AI in system operation and control enhancing diagnostics, troubleshooting, and preventive maintenance [281]. Hence, the suggested roadmap aims to integrate prognostics into maintenance, enabling the anticipation of failures before they occur. This constitutes an improved predictive maintenance strategy bolstered by information platforms and AR/AI-based fault diagnosing strategies.

9.5.3. *Information supply*

The volume of data collected is rapidly increasing due to digitization in the rail sector and a growing number of sensors in rolling stock. Access to database platforms enables data storage, management, off-site analysis, and real-time maintenance support [282]. Various approaches can be used for processing and analysing maintenance data to convey various aspects of rolling stock conditions and for operators supporting functional decisions [283]. The roadmap outlines the procedures stored in the database platforms required for conveying organized information to the AR technology. It specifies the types of information gathered, including online and offline maintenance data and system information, and elucidates the methods for data storage and processing.

9.5.4. *AR technology*

Building an AR system from the ground up is challenging and time-consuming and most research focus on high-level applications rather than low-level implementations [280]. AR systems must be updated, supported by task-relevant data, and have context awareness to be useful. AR can be experienced through AR glasses, smartphones and tablets where AR experiences can be supported by motion tracking, environmental understanding, anchors, cloud-based services for creating and managing 3D targets, and real-time 3D tracking of real-world objects [280]. The UI design should support seamless interaction and be intuitive to the operator. The roadmap incorporates general characteristics of AR technology that the organization must adhere to, covering aspects such as hardware/software, UI design, contextualization, 3D visualization, ergonomics, and connectivity. These characteristics can subsequently be tailored to suit the specific needs of the organization.

9.5.5. Operational requirement

Stakeholders must align with the overarching transformation goals and actively participate in fostering a culture of social dialogue [284]. Stakeholder and inter-departmental collaboration encompasses facilitative processes that empower various stakeholders to openly express their needs, expectations, and potential conflicts of interest. Collaborative efforts support the AR design and implementation of essential frameworks, industry policies, innovations, and reskilling of personnel. Good corporate governance is indispensable to support transparency, business integrity, and accountability [285]. AR not only impacts the operational maintenance aspect of an organization but also requires adaptations to the existing database architecture. This entails the development of suitable strategies, standards, and regulations. Rolling stock organizations need to incorporate additional rules and regulations to harmonize and align their operations with the objectives of AR in maintenance. These objectives encompass aspects like human-AR interaction and data management [286].

9.6 Step IV & Step V: "Case study" & "Evaluation and presentation of results"

The AR roadmap proposed in this study is employed to assess what directions and requirements are needed for a rolling stock organization. NS is active in the public transportation sector and has grown to become an important partner for transport companies and owners of rolling stock, well beyond the borders of the Netherlands [25]. Among different services, NS is responsible for maintenance, cleaning, and refurbishing rolling stock. Currently, NS is exploring applications of AR for rolling stock maintenance. This case study is designed to conduct a readiness and maturity assessment for a rolling stock organization. After this has been determined, the AR roadmap can be validated. The AR roadmap is validated to see whether the organization is capable of implementing AR for rolling stock system failures.

9.6.1. Focus group

The target group for AR in rolling stock organizations for analysing the readiness and maturity of an organization is interdepartmental and requires input from IT/OT managers, maintenance and operational experts, as well as innovation managers. In this work, 11 experts from NS filled in the questionnaire and participated in the semi-structured interview, 5 experts were involved in validating the AR roadmap via prototype testing in an online workshop.

9.6.2. *Maturity and readiness assessment in a rolling stock organization*

The scores corresponding to the answers given to the online questionnaire revealed that the rolling stock organization has an overall maturity score of 2.9 on a scale of 1 to 5. This score indicates that there is room for improvement, and the organization may need to enhance its capabilities to fully realize the benefits of AR in maintenance. AR services are compatible with digital business models which are supported with resources at a medium level. The organization has partnerships with some stakeholders and launched pilot initiatives. The leadership team is investigating potential benefits and plans to invest. The organization allocates a medium level of budget to technologies and investments are made in a few operational operations; cost/benefit analyses are not conducted. Organizational structure is suitable for initial projects. Central IT departments exist in the company where there are limited environments where IT/OT units collaborate. Departments are open to cross-company collaboration to drive improvements. Figure 9.5 presents a radar chart for all maturity dimensions resulting from the online questionnaire. Appendix III presents a summary of the information concluded from the semi-structured interviews.

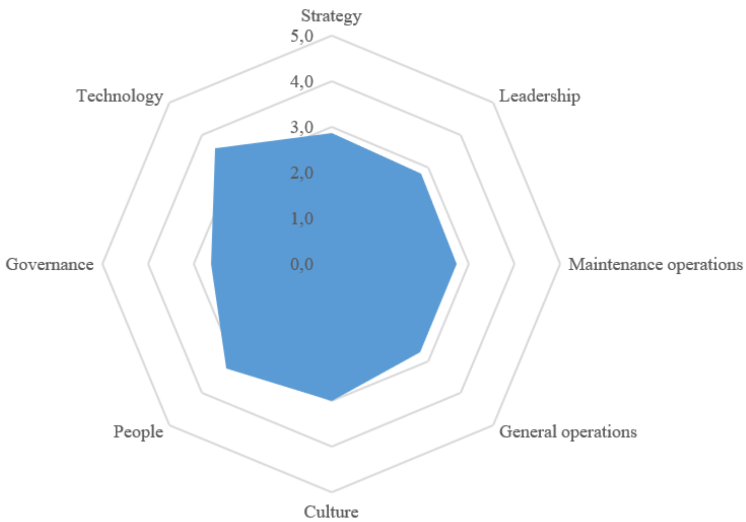


Figure 9.5. Overall score: Maturity and readiness assessment.

9.6.3. *AR roadmap validation*

NS aims to initiate a pilot SARA project, aiming to address rolling stock system failures through AR solutions. The successful launch of such a project necessitates the formulation of an AR technology adoption strategy. To validate the roadmap, a common sanitary rolling stock system failure of the VIRM-m1, a refurbished double-decker rolling stock series [107], is utilized to create the SARA prototype dedicated roadmap. Operational data collected in real-time from 87 rolling stock sets reveals 1461 instances of sanitary system failures over three months. Failures in this subsystem significantly impact rolling stock operations, necessitating the removal of the affected rolling stock from service. The sanitary system consists of the vacuum toilet and the bioreactor. Upon entry into the maintenance facility, operators initiate tests and trials to evaluate the justification of the sanitary failure in the rolling stock. Subsequently, the operator proceeds with a fault diagnosis and carries out the maintenance actions accordingly. Nevertheless, due to the absence of standardized maintenance procedures for this system error, the operator resorts to a random troubleshooting procedure.

The SARA prototype roadmap provides an illustrative framework for the AR roadmap, specifically showcasing the implementation of sequential assistance in maintenance procedures for rolling stock organizations (Figure 9.6). The SARA prototype roadmap is composed by previous thesis chapters and supports the pilot project by depicting the relevant components for sequential AR assistance by, (1) stating the required support from employees, e.g. knowledge management and sharing (chapters 3 and 4), (2) defining the requirements for data and IT architecture, e.g. utilization of maintenance manuals, real-time operational data, existing FTA and FMEA (chapters 5 and 6), (3) setting AR technology requirements, e.g. 3D visualizations, utilizing of an easy interpretable design, contextualizing of failure information, and embedding the system safely in the maintenance work (chapters 7 and 8), and (4) incorporating accurate leadership, e.g. incorporating governance rules and regulations, defining a clear strategy, and making resources available (Table 9.1).

The SARA prototype roadmap is validated in a workshop, the requisites are:

- Information supply is based on mostly existing standardized online and offline maintenance procedures. Centralizing all maintenance and system information ensures all relevant information is fed to the AR technology. The AR roadmap emphasizes the importance of having correct and sufficient maintenance data information for adequate troubleshooting.
- The AR technology requires a stable internet connection for online support, safe working conditions, intuitive and clear 3D visualizations mapping the location by providing system information, and interpretable and easy-to-use holographic support to operators.
- Organizational impact on the roadmap reflects on leadership and management having a clear vision of the future. A pilot project tests the feasibility, functionality, and potential impact before full-scale deployment and requires data management, collection, and feedback for future funding.

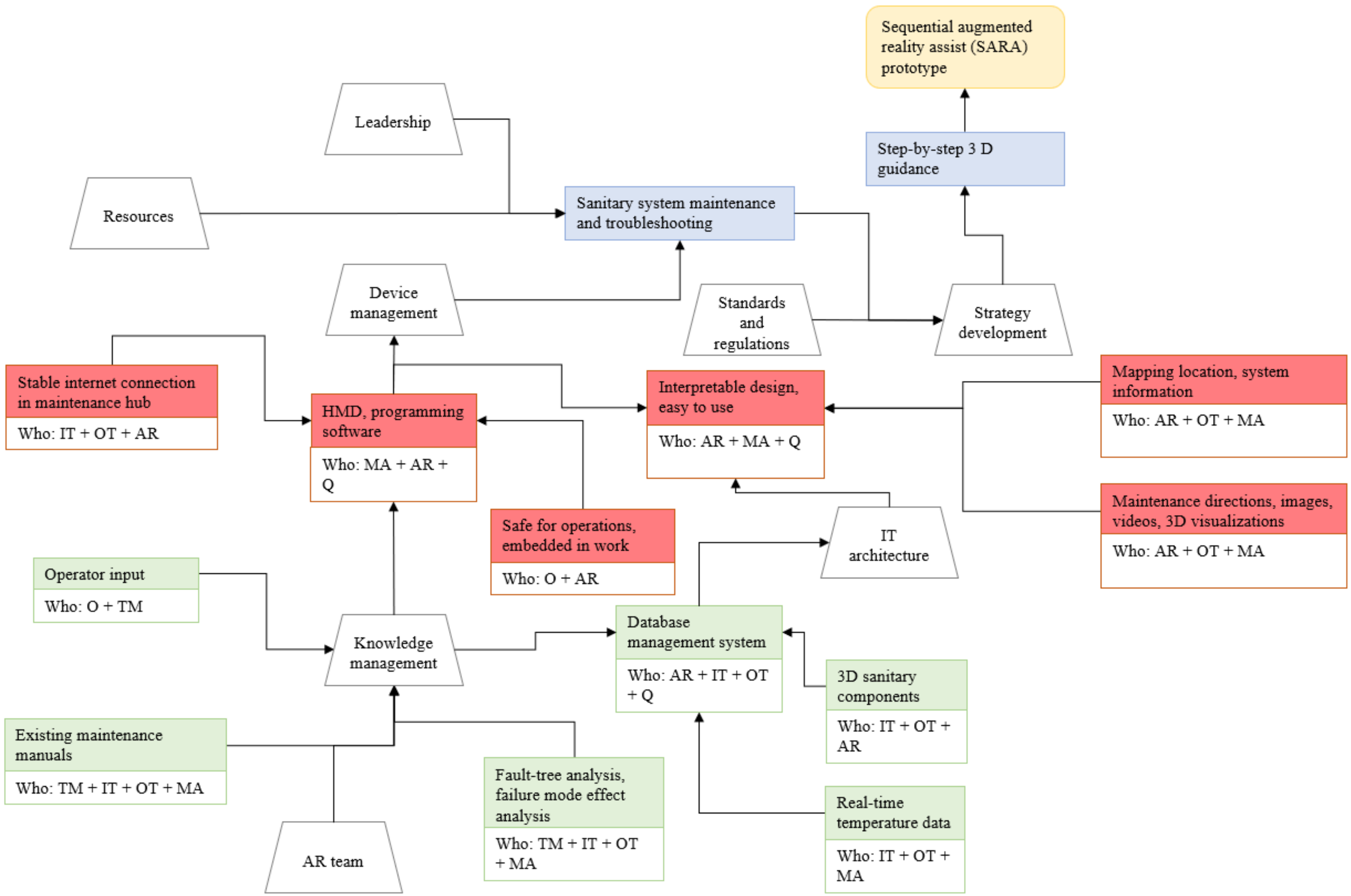


Figure 9.6. SARA prototype roadmap.

9.7 Conclusion and discussion

Maintenance procedures can be supported by AR by enhancing visualization, providing real-time data, improving training, increasing safety, and contributing to general operations. While academia exponentially examines the real-world applications of AR in organizations via case studies, the adaptation and implementation of AR in existing maintenance operations is inherent involuntarily. To incorporate AR in rolling stock organizations, an AR roadmap is needed to state interrelationships between the technology, existing IT infrastructure, maintenance procedures, company culture, and readiness and maturity of the rail sector.

In this work, the dimensions and items required for a readiness and maturity model for AR in rolling stock organizations are discussed. Based on the literature, eight dimensions and 39 measurement items were determined. By collecting subjective judgements of experts, the relevance of the dimensions and measurement items can be evaluated in a rolling stock organization. Three-level staged ISM method supports identifying the interrelated connections required for AR implementation in rolling stock organizations. Combining a maturity model and ISM supports understanding the intricate relationship between the AR technology and organizational aspects in the maintenance strategy of a rolling stock organization and contributes to a structured AR-based roadmap. A general AR roadmap consisting of five levels is developed to support organizations in developing multiple AR solutions.

From the presented findings, it can be concluded that the AR roadmap is an effective tool for rolling stock organizations, assisting them in assessing their current position and guiding their journey toward advanced AR applications, ranging from remote support to intelligent assistance. The application of the proposed AR roadmap in a Dutch rolling stock organization, with input from 11 experts, demonstrated the organization's positive trajectory toward mature AR adoption, especially excelling in technology and people-related aspects. Specific attention is identified for improvement in governance and general operations, emphasizing their need for defining regulations, technology standards, and enhancing interdepartmental collaborations. The validation through a case study involving a rolling stock system failure further supports the effectiveness of the AR roadmap in practical maintenance scenarios.

Overall, this study fills a gap in the perceived benefits of implementing AR in maintenance for rolling stock organizations by providing an AR roadmap structuring contextual relationships. However, this has not been without limitations opening insights into future work. Traditional approaches for analysing maturity models deploy weighted scores, mean values, and relative importance index for the maturity dimensions and measurement items. To address this, ISM methods are more suitable for studies involving limited experts compared to the traditional approaches. This study is limited by the bias of experts who define the outcome of the AR roadmap. Contextual relationships depend on expert feedback, this was moderated by ensuring adequacy in the expertise of the participants. This is done by intentionally selecting participants who are well aware of the organization's AR applications, digital innovation journey, and maintenance knowledge.

Implementing an AR roadmap in organizations offers numerous benefits and supports maintenance work by providing real-time information, step-by-step maintenance instructions, and visual support while incorporating organizational aspects, such as leadership, company culture, and maintenance procedures. Limitations of utilizing an AR-based roadmap relate to the obsolescence risk as organizations need to adapt to rapid technological advancements. AR may be limited in certain maintenance scenarios, therefore, finding a suitable application case is key. Regularly maintaining and updating AR content can be resource-intensive and requires dedicated AR teams. Organizations need to carefully assess limitations and address them strategically to maximize the benefits of implementing an AR roadmap. Regular evaluation and adaptation of the roadmap mitigates challenges and enhances the overall success of AR integration. Future work lies in exploring synergies with emerging technologies such as ML and the IoT to enhance automizing AR applications. Furthermore, engagement with the broader AR community and industrial partners is encouraged to share experiences, best practices, and lessons learned. The AR roadmap should increase its scalability on a national and global scale.

Chapter 10 – Discussion and conclusion

As stated in the introduction and expounded upon in the subsequent chapters, AR plays a significant role in addressing challenges related to troubleshooting and maintaining IT/OT converged systems within the railway industry. This chapter serves as a self-contained conclusion, offering a comprehensive overview of the essential insights in this thesis. The structure of the chapter prioritises the discussion of formulated research questions, followed by an exploration of key limitations in this research. Finally, potential avenues for future research are outlined.

10.1 Research objective conclusion

The research described in this dissertation set out to address the Main RQ faced by the railway industry that is responsible for troubleshooting and maintaining IT/OT converged rolling stock systems using AR:

"How to use AR to support operators in troubleshooting and maintaining IT/OT converged rolling stock systems faced by the railway industry?"

This question has been investigated and answered throughout the last eight chapters (chapters 2-9), by following a mixed-method pragmatic approach of implementation and evaluation of the designed solutions. This approach delves into practical implementation while remaining rooted in theoretical underpinnings. The methodology traverses through contextual reviews, case study analyses, and iterative design processes, ensuring a robust foundation for developing AR solutions tailored to the nuanced needs of maintenance operations in the railway industry. The data and information collected and processed during these design cycles were integrated into the design artefact and implemented at a railway company. By reflecting on the design and application of these artefacts in their real-world context, it is possible to draw conclusions and recommendations, effectively answering the 'how'-type question based on the research findings. By designing AR troubleshooting instruments for IT/OT converged systems at NS, it became apparent that maintaining digitized and computer-driven systems and procedures has specific goals and preferences that require a novel troubleshooting approach, leading to a research gap.

The research identifies a gap in the existing literature, where AR for troubleshooting IT/OT rolling stock failures has not been extensively explored. The research introduces a method grounded in integrating AR, information systems and maintenance principles to address the challenges of troubleshooting IT/OT system failures (Chapter 2). AR can seamlessly integrate into existing IT/OT infrastructure of rolling stock systems, ensuring compatibility and efficient data exchange. This research contributes to the research gap by proposing an innovative approach that integrates AR, AI, and a centralized data platform (Chapters 5 and 6) to automate diagnosis, inspections, failure predictions, and decision-making (Chapters 4 and 7) in the context of rolling stock maintenance. The importance of human involvement and interpretation of results is emphasized to ensure the reliability and effectiveness of AR systems (Chapters 3 and 8). This research enhances operator support by providing real-time, contextual, and customized data based on the operator's expertise and experience. Adaptive UI displaying only relevant functions and 3D maintenance information of the troubleshooting process improves the usability and understanding of the failures to operators. Providing step-by-step guidance on the troubleshooting and maintenance procedure supports the decision-making by providing in-depth knowledge of the IT/OT system failure.

Through a four-year collaboration with stakeholders in the Dutch railway sector, the study gains sector-specific insights. The gained insights regarding the challenges and opportunities associated with utilizing AR troubleshooting to support operators contribute to a deeper understanding of the unique requirements and dynamics of the railway industry. The study conducts thorough case studies to identify issues related to AR in maintenance, designs an AR troubleshooting tool, and formulates an AR organizational roadmap (Chapter 9). An AR roadmap supports organizations in adapting and implementing AR in current maintenance procedures by considering challenges and success factors. The methodologies utilized across the chapters, encompassing both qualitative and quantitative data, constitute a mixed-method pragmatic approach. These methodologies serve as connectors to all frameworks presented in the chapters, including the adaptive architectural framework and AR database architecture, fostering a cohesive and integrated research process. In addition, the methodologies and frameworks developed in this research are generalizable and adaptable to other industries facing similar IT/OT challenges. By offering scalable solutions and best practices, this research extends its impact beyond the railway sector to a broader range of industrial contexts.

Overall, AR-based troubleshooting systems offer a more streamlined, intuitive, and efficient approach to maintaining IT/OT converged rolling stock systems compared to non-AR systems. AR enhances the capabilities of operators in troubleshooting and maintaining IT/OT converged rolling stock systems by providing real-time information, contextualized and visualized instructions, and improved decision support. This instantaneous access to information significantly reduces the time required to diagnose and address maintenance issues. By superimposing digital information onto physical components, AR guides operators through complex maintenance tasks step-by-step, reducing the likelihood of errors and enhancing the accuracy of their actions. The visual guidance can be particularly beneficial for troubleshooting tasks that involve intricate systems or components. The integration of AR with AI and centralized data platform systems contributes to the automation of maintenance processes, making operations more efficient and adaptive to evolving industry needs. This centralized approach streamlines communication and decision-making processes. The continuous refinement and adaption of AR-based tools ensure their effectiveness and applicability in diverse industrial contexts.

10.2 Sub-research questions conclusion

This section provides a detailed overview of the answers provided in this thesis to the formulated subRQs.

10.2.1. SubRQ1: What are the current state, research challenges, and future directions for using AR for IT/OT failures in the maintenance operations of digitized rolling stock?

The railway industry is undergoing digital transformation, focusing on achieving safer, higher quality, and more sustainable transport and maintenance operations. The digitization of rolling stock results in the convergence of IT and OT systems increasing the complexity of systems and leading to unpredictable and intricate failures within converged systems. Challenges include a lack of understanding of failures, limited IT knowledge, and disjointed collaboration between IT and maintenance departments in railway organizations. Moreover, challenges related to data gathering and management and the transition to digitizing maintenance operations occur. AR is identified as a valuable tool for addressing IT/OT failures in digitized rolling stock, offering potential applications such as fault detection and remote support (Figure 10.1).

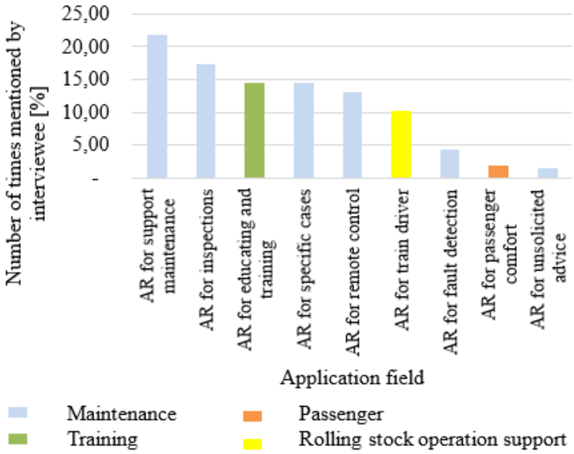


Figure 10.1. Potential AR applications based on qualitative field study (Chapter 2).

Chapter 2 emphasizes the need for collaboration between stakeholders and suggests that AR can support maintenance operations by identifying, structuring, and providing solutions to IT/OT failures in digitized rolling stock. The implementation and evaluation of AR technology in real-world scenarios are considered important for future research.

10.2.2. SubRQ2: How to incorporate the operator's perspective for AR troubleshooting and support decision-making procedures in maintenance operation?

The increasing complexity of failures, coupled with limited time for maintenance, makes efficient decision-making challenging. The integration of AR aims to support operators by visualizing information, guiding troubleshooting procedures, and recording maintenance activities for future procedures. AR provides real-time visual guidance and helps understand complex systems by supporting troubleshooting and decision-making. Chapter 3 underpins that operators have varying levels of expertise. AR systems should provide information at a level suitable for both novice and experienced operators, involving the cognitive load of the information presented by minimizing the need for manual information search and interpretation. The AR system should support collaborative work between operators and interactive technology. Incorporating User-Centric Design (UCD) helps in understanding the operator's needs, preferences, expectations, and learning capabilities. Allowing operators to customize the AR UI to their preference supports alignment with the operator's mental preferences by choosing what information is displayed, how it is displayed and what level of detail is required. The AR technology requires seamless integration into the daily workflow of maintenance operations. Real-time contextualized information supports operators by supplying information as tasks are performed. Offering an adaptive AR tool caters for the dynamic nature of maintenance operations and is based on operator feedback, changing maintenance conditions, and emerging requirements. A structured process for using the adaptive AR tool captures the know-how and helpful tips of experienced operators, adapting the information to different contexts, and ensuring that the tool remains relevant over time. Therefore, an adaptive architectural framework is proposed that combines AR features for knowledge capture, maintenance support, and system failure analysis (Figure 10.2). The AR tool should capture the knowledge of the operator for future learning. A case study explores the application of the framework in the maintenance of a retractable step of a rolling stock.

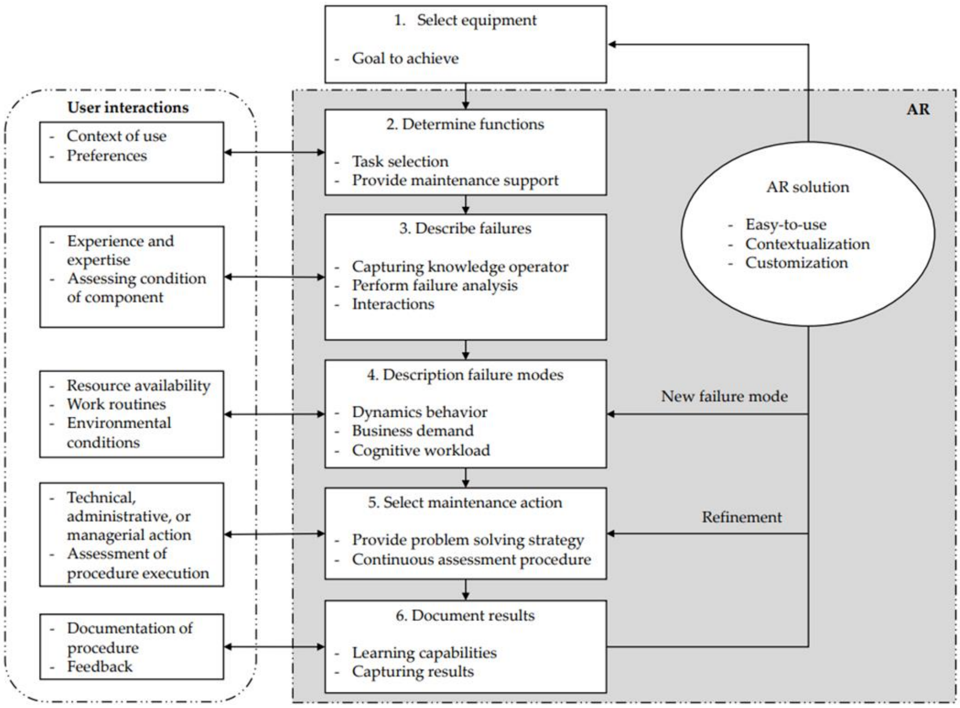


Figure 10.2. Schematic of the adaptive architectural framework (Chapter 3).

In Chapter 4 an AR tool for comprehending IT/OT system failures is created, assisting in troubleshooting, and recording maintenance activities and execution time for procedure development. The research involves a qualitative field study, including interviews, workshops, and a case study at the railway company NS. The AR decision-making tool is designed with a centralized data platform (Figure 10.3), object recognition, system reference, and AR visualization. In addition, the tool utilizes existing FMEA, FTA, and what-if-analysis to guide operators through decision-making.

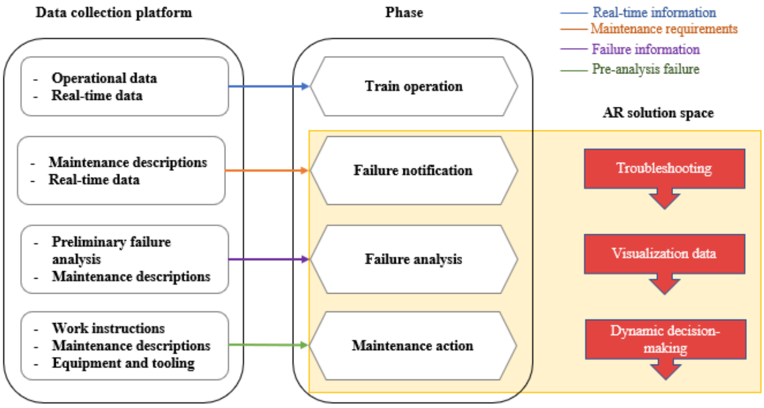


Figure 10.3. Schematic of the adaptive architectural framework (Chapter 4).

The key contributions are: (1) receiving processed information from a server, (2) using object recognition for system reference, (3) presenting a list of failures and associated maintenance actions, (4) guiding the operator through what-if-analysis checklist, and (5) recording time and activity for completing the maintenance tasks.

10.2.3. SubRQ3: What criteria govern AR to collect, structure, predict, and troubleshoot IT/OT failures by combining CPS with AI, and case-based reasoning?

The integration of AR, AI, and KBS creates a comprehensive system for automatic fault detection and troubleshooting in complex industrial environments, contributing to more efficient maintenance operations as discussed in Chapter 5. The criteria governing AR functions include providing real-time information, visualizing and contextualizing data, enabling object recognition, and remote control. AI, particularly ML/DL, analyses extensive datasets to automatically diagnose machine states and predict failures in advance and acts as the brain of the system using rule interpretation and ML/DL models to forward chaining algorithms. KBS captures, formalizes, and incorporates expert knowledge for complex maintenance tasks and requires continuous input from operators. A dynamic reference map connects AR, AI, and KBS creating a cohesive system for automatic fault detection being supported via an AR UI to include maintenance directions by exploiting clear graphical interfaces (Figure 10.4).

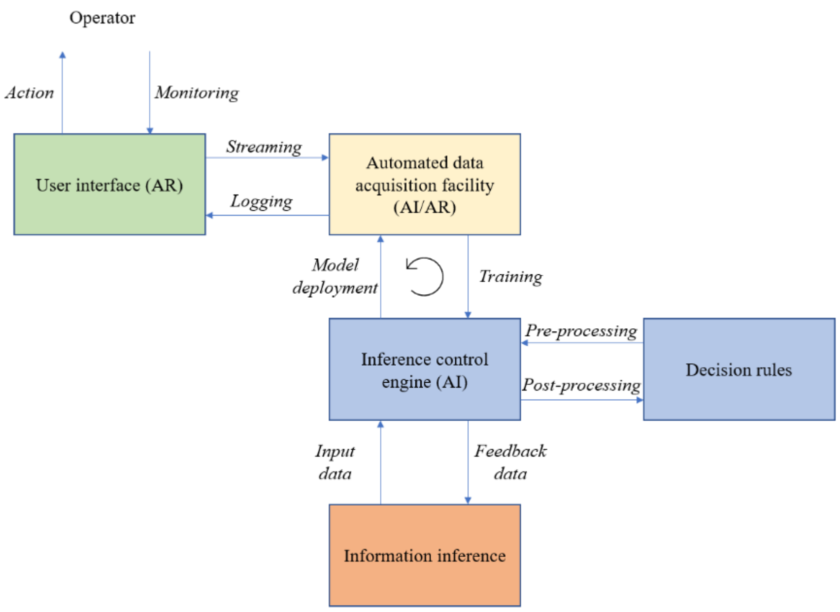


Figure 10.4. Dynamic reference map (Chapter 5).

Exploiting ML/DL approaches requires large datasets from machines to train the models. Based on the characteristics of the dataset the ML/DL model is chosen. Chapter 5 demonstrates the dynamic reference map through a case study that automatically detects a failure using AR, AI, and KBS for troubleshooting by creating a demonstrator. Feedback from operators regarding the demonstrators includes the following key points: (1) the demonstrator effectively facilitates clear identification of failures, (2) it offers easily understandable maintenance instructions, and (3) it contributes to a reduction in errors associated with manual troubleshooting. The research has implications for organizational data infrastructure which must be in synergy with the troubleshooting method.

Chapter 6 outlines the integration of AR within an innovative database architecture for troubleshooting IT/OT failures in the railway industry and involves several criteria and building blocks (Figure 10.5).

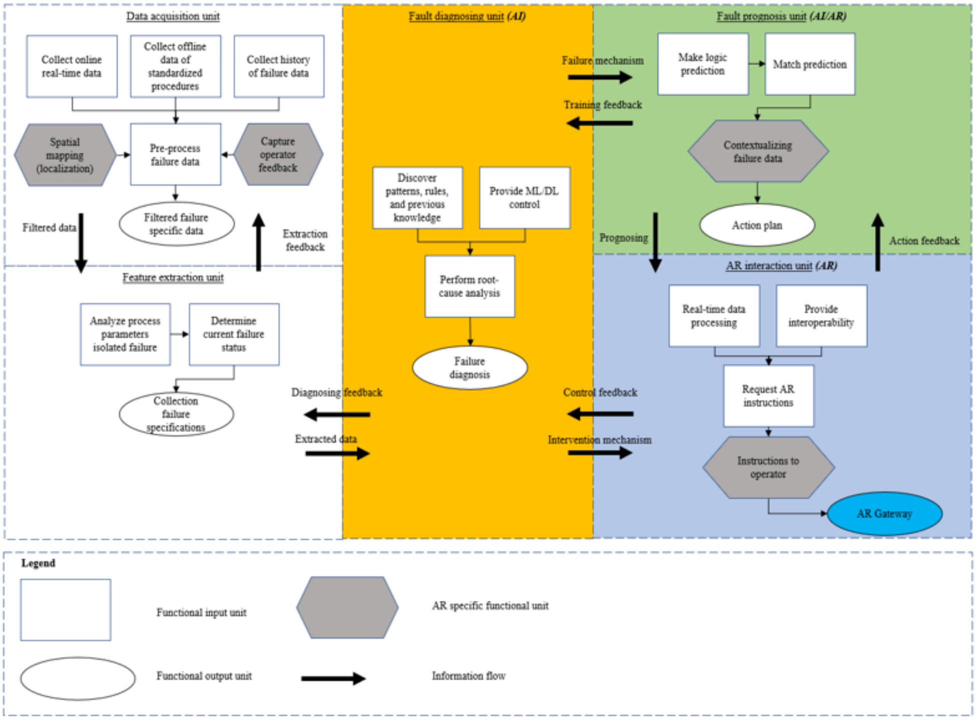


Figure 10.5. AR database architecture (Chapter 6).

This database architecture combines CPS, ML approaches, and case-based reasoning to display maintenance information through AR by providing a common data model for different building blocks, allowing centralized and efficient management of data. The building blocks are integrating five units and require integration of maintenance procedures with different levels of automation and easy sharing of maintenance events by focusing on data gathering and processing, fault diagnosis, and visualization. The units utilize ML models (SVM, NB, LR) for failure classification and are supported by AR for data capturing, spatial mapping, and presenting fault diagnosis in AR for real-world troubleshooting scenarios. The building blocks and their specifications are:

- Data acquisition unit consists of (1) collecting online and offline data, including real-time operational and historical maintenance data (2) pre-processing data for spatial mapping, (3) capturing operator feedback for knowledge sharing, (3) filtering failure data based on predefined fault rules set by designers.
- Feature extraction unit analyses maintenance failure data to isolate the failure parameters and characteristics and extracts data characteristics to obtain the current failure status and its specifications, it is ideally based on ML methods to minimise the human involvement.
- Fault diagnosing unit applies intelligent fault diagnosing using ML methods to automatically recognize the health state of machines. In addition, it discovers maintenance patterns and system failures, levering operator knowledge for pattern comparison. ML control and case-based reasoning for RCA of failures are utilized.

- Fault prognosis unit produces and decides on action items, which may involve automatic intervention or operator decision-making by comparing and matching the logic behind a failure mechanism with pre-defined problem-solving action plans. Contextualized failure data in AR provides real-time support to operators.
- AR interaction unit incorporates all interactions between the database architecture, AR technology, and the maintenance operator. It deploys a gateway to visualize the maintenance instructions.

Chapter 6 describes a case study on the implementation of the AR database architecture in NS to troubleshoot IT/OT failures in rolling stock maintenance. The case study employs sequential pattern mining to analyse unstructured data, including fuzzy and unclassified information. MPD is combined with NLP for feature extraction. In summary, the case study shows the integration of AR and database architecture for troubleshooting IT/OT failures in rolling stock maintenance. The results emphasize the importance of reliable data, operator input, and the potential of combining AR and AI technologies. The proposed database architecture serves as a reference for smart technology control in organizations.

10.2.4. SubRQ4: What design and functionality specifications ensure the interaction in AR to troubleshoot rolling stock system failures and enhance human-AR maintenance procedures?

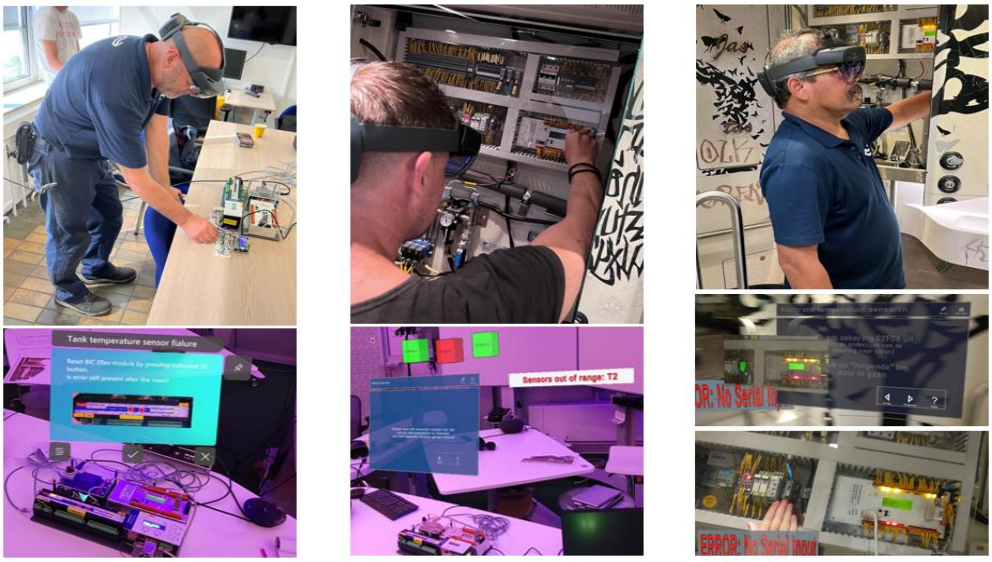
To ensure effective interaction in AR for troubleshooting rolling stock system failures and enhancing human-AR collaboration a combination of three components is key: functional requirement, operator role, and UI experience (Table 10.1). The specifications follow from Chapter 7 and Chapter 8 and aim to ensure that the AR troubleshooting system is not only technically advanced but also user-friendly and adaptable to the specific challenges and requirements of rolling stock maintenance.

Table 10.1. Design interactions in AR

Design interactions in AR	Specifications
Functional requirements	1. Data collection and processing, developing a centralized data platform for collecting, filtering, and structuring system failure data. Implementing NLP for pattern mining.
	2. Real-time data integration for continuous availability of maintenance and rolling stock information.
	3. Fault diagnosing by utilizing ML methods for fault detection, recognition, and identification of system failure.
	4. Visualization and contextualization by providing a 3D representation of maintenance activities and enabling system reference to operators. Object recognition matches input against predefined rules and patterns to determine the appropriate maintenance response.
	5. Enabling user interaction with the 3D AR projection through gestures, voice commands, or other intuitive methods. Operators can inspect the current health state of

Design interactions in AR	Specifications
	the rolling stock and request procedural details by exploiting real-time data.
	6. Accessing, logging, and storing relevant maintenance data for analysis and future reference supports planning and scheduling future maintenance activities.
	7. The AR troubleshooting system should maintain flexibility to adapt to changing user needs and emerging technology advancements. Seamless integration and compatibility with existing maintenance systems and IT structures is key.
Operator role	1. Design an intuitive AR UI experience aligning the physical and virtual world and use simple gestures for translation, rotation, and interaction with virtual objects.
	2. Providing realistic troubleshooting scenarios enhances the system recognition and represents the actual system components under investigation.
	3. Hardware and software integration may limit the UI experience. The AR application should be scalable and applicable across different devices.
UI experience	1. Design gestures for translating, rotating, and interacting with virtual objects that are not only intuitive but also across different viewing angles and distances.
	2. Minimalistic design avoids presenting cluttered information to the operator. Seek operator input for colour, motion, distance, and resolution in design solutions.
	3. Simplification of maintenance tasks supports information transfer and reduces cognitive load.

Chapter 8 provides design guidelines for troubleshooting rolling stock system failures with a focus on human-centred design and iterative prototyping (Figure 10.6). The process involves three stages: (1) the initial stage for creating awareness, (2) the hand-over stage for defining use cases and developing prototypes, and (3) the practice stage for iterative testing in real-life scenarios. A sanitary system failure case study presented in Chapter 8 highlights the importance of having real-time data in troubleshooting, utilizing prototyping to address the functional, UI, and operator requirements iteratively, and incorporating operator feedback for refining the prototypes. The AR troubleshooting functionality requires a data-oriented AR UI paradigm involving collecting, structuring, and extracting real-time data, discovering maintenance patterns, contextualizing and visualizing maintenance instructions, and automating data structuring. The AR UI must display filtered and tailored information in a structured and aligned manner and provide an engaging experience by simulating real troubleshooting scenarios. The AR UI background and colour schemes should be customized to the operator's preferences. Intuitive and minimalistic 3D visualizations guide operators easily through problem-solving strategies with minimal overload and distractions involving FMEA, FTA, RCA, and case-based reasoning.



(a) (b) (c)

Figure 10.6. AR UI and operators working with the troubleshooting prototypes (a) exploratory prototype, (b) experimental prototype, and (c) evolutionary prototype (Chapter 8).

10.2.5. SubRQ5: What organizational obstacles, requirements, and viewpoints do stakeholders have concerning the implementation of AR in railway organizations?

Chapter 9 discloses the organizational obstacles faced by railway organizations which are: (1) lack of clear vision and a roadmap, e.g. a roadmap development process supports creating a clear vision for the future in rolling stock maintenance, (2) insufficient resources, e.g. organizations may allocate adequate resources for AR realizations including pre-stated investments, (3) resistance to change, e.g. company culture may resist technological change whereas fostering a culture of continuous improvement and openness to innovation to align with AR adoption is key, (4) intellectual property concerns, e.g. establishing clear guidelines and practices for managing and protecting intellectual property in the context of AR is required, (5) misalignment of IT and data infrastructure, e.g. seamless integration of AR in existing work environments and data infrastructures is needed. To overcome the organizational obstacles, an AR roadmap is provided to meet operational and technological requirements and promote a seamless integration of AR into existing systems in rolling stock maintenance operations (Figure 10.7). The proposed AR roadmap covers various dimensions, including AR journey, operational task, information supply, AR technology, and organizational requirements.

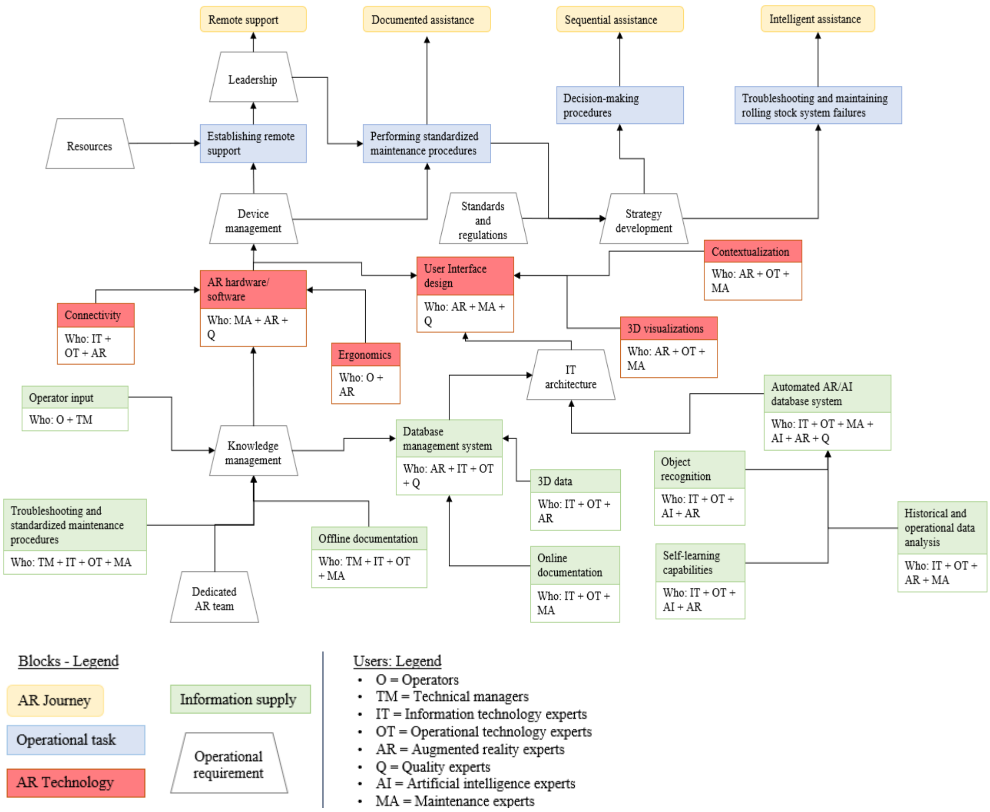


Figure 10.7. AR roadmap for rolling stock organizations (Chapter 9).

Moreover, chapter 9 incorporates a case study involving NS to assess the readiness and maturity for implementing AR in rolling stock maintenance. There is a need for dedicated teams responsible for AR-specific work, supported by a centralized platform for online and offline maintenance and operational documentation. Enhancing collaboration between IT and OT departments is key for successful AR integration. Motivating employees can be challenging, showing the potential and capturing and sharing knowledge can help in motivating employees. Employees are willing to invest time and effort in technology advancements when they see the importance and expect benefits related to maintenance efficiency, quality, and problem-solving. New AR-related standards are expected to be created and documented regarding cybersecurity, safety, hardware, intellectual property, and privacy standards. Railway organizations face challenges in the IT infrastructure for AR usage, such as programming. Addressing the challenges and requirements will be crucial for the successful implementation of AR in railway organizations.

10.3 Discussion and limitations

Like any other research result, the outcome of the PhD research presented in this dissertation has inherent limitations. In each of the chapters (chapters 2-9), specific limitations have already been addressed. This section, therefore, focuses on discussing the most important limitations that apply to the entire PhD research project. The limitations are divided into general limitations related to a single-organization perspective and research implementations.

10.3.1. Generalization limitations single-organization perspective

A significant part of the study has been conducted within the confines of the Dutch railway company NS, encompassing both the development and assessment phase of an AR troubleshooting prototype. This focused approach offers distinct advantages over a detached research strategy, providing an opportunity for a thorough, context-rich, and empirical comprehension of the research strategy. The depth of engagement is conducive to generating knowledge that is both theoretically robust and practically applicable. Nevertheless, focusing on a single organization introduces a noteworthy methodological challenge, given the potential difficulty in generalizing findings from a singular case.

Throughout the PhD research, efforts were made to leverage the benefits inherent in a detailed investigation, while simultaneously acknowledging and addressing the challenges associated with generalization from a singular case study. Using multiple methods or data sources to enrich the research process helps to mitigate biases inherent in single-method, single-observer, or single-theory studies. This approach involves combining multiple data sources, engaging diverse observers, considering distinct theories, employing varied methods, and incorporating diverse empirical perspectives [287][288]. This includes the examination of different asset types (such as various rolling stock types and distinct case studies) and the provision of a wide spectrum of decision contexts across different departments. The strategies and methodologies proposed in this study have their roots in specific theoretical frameworks but are designed to be examined and deliberated from various theoretical standpoints, resulting in a hybrid AR solution. The study is conducted in active collaboration with multiple observers. The evaluation of AR troubleshooting prototypes and decision-support tools involves multidisciplinary groups with three or more individuals, ensuring a diverse perspective. Furthermore, research findings are discussed in steering group meetings attended by university researchers and NS staff.

10.3.2. Limitations of research implementation

Several research findings were not thoroughly put into practice and their effectiveness in practice was therefore not studied in detail. These include the need to reach organizational compatibility, operator input dependency, data availability and processing limitations, and technology requirements including synchronizing and connecting real-time train data for AR utilization.

Organizational compatibility issues are caused by (1) the existing IT and OT systems may not seamlessly integrate with the AR technology, (2) AR hardware requirements are not compatible with the existing infrastructure or third-party systems (maintenance management software), (3) employees may resist adopting new technologies, (4) AR solutions require customization to specific user and rolling stock requirements, and (5) organizations may have reservations about the security of sensitive IT/OT data when accessed through AR devices. To overcome these organizational limitations, railway organizations should undertake a comprehensive assessment of their existing infrastructure, invest in necessary technologies, prioritize data quality assurance, and foster a culture that embraces technological advancements. Collaboration between IT, operations, and other relevant departments is essential for addressing these challenges and successfully integrating real-time data into AR troubleshooting processes. Operator input becomes crucial not only for troubleshooting but also for validating and enriching the system's knowledge base. Additionally, efforts should be made to enhance data quality, diversity, and volume to improve the overall performance of AR troubleshooting systems.

Finally, the artefacts should be tested on a larger scale in real-world applications to improve the effectiveness and generalisability of the presented results.

10.4 Future research

Future work in the realm of using AR for troubleshooting and maintaining IT/OT converged rolling stock involves refining and extending AR technological capabilities based on real-world applications and evolving operational requirements. Also, potential areas for further research and extension of the developed artefacts are mentioned. To test the performance of the presented artefacts in other industries, several suitable industrial areas for future work are mentioned.

10.4.1. AR technology capabilities

Future work should focus on conducting rigorous validation studies using real-world data and scenarios to assess the performance and effectiveness of developed frameworks and artefacts in practical settings. This may involve conducting field trials, user studies, and performance evaluations to collect empirical evidence and validate the accuracy, efficiency, and usability of the system.

Further investigation and identification of additional technology adoption patterns considering challenges and success factors is key including the exploration of different hardware and software solutions for adaptive instructions to maintenance operators. Focus on providing real-time, contextualized, and customized data to operators based on their experience supports Operator 4.0 requirements by the exploration of adaptive UI that shows only relevant functions to the maintenance operators, improving its usability. Exploration of automatic data-capturing processes, including the development of a framework for knowledge capturing and transforming, supports dynamic feedback systems in maintenance operations. Continuous follow-up on the research's journey, tracking its progress and addressing any emerging challenges while engaging managers and organizations to expand the research's applicability and gather diverse insights is key.

10.4.2. Research for technological artefacts

To achieve a thorough assessment of the created technological artefacts, forthcoming studies might explore longitudinal and cross-sectional approaches. The design rationale employed for the developed technological artefacts can be replicated in different settings to enhance the applicability of the findings. The suggested AR prototype could undergo testing in an extensive pilot initiative. The centralized data platform proposed could be enhanced to facilitate novel technology advancements within railway organizations. Lastly, it is recommended to integrate a combination of the artefacts into real-world applications.

10.4.3. Industrial context variation

To more broadly evaluate the efficiency and effectiveness of the proposed conceptual and technological artefacts, future research may test these artefacts in other industrial areas. A possible candidate in this regard is AR troubleshooting at the interface of manufacturing and commissioning in different transportation sectors. The core of manufacturing and commissioning lies in production, where precision, speed, and quality of IT/OT interfaces converge. AR troubleshooting aids this core by providing real-time assembly and commissioning instructions directly overlaid on the actual products. With AR, inspectors get instant visual checks against predefined product standards. Any discrepancies are immediately highlighted, ensuring that only products meeting the highest quality thresholds move forward in the production chain. Finally, AR contributes to training and educating novel operators in immersive industrial training programs. Consequently, the artefact can also be evaluated in these domains.

Chapter 11 – Appendices

Appendix I

Table A.I.1 presents the online questionnaire.

Table A.I.1. Online questionnaire.

Statement	1 = No AR vision 5 = Integrated in organization				
The organization has a clear AR technology vision and roadmap for the future	1	2	3	4	5
The organization has available resources for AR realization	1	2	3	4	5
AR activities are documented and communicated in the organization	1	2	3	4	5
AR activities are purposefully planned, coordinated, and implemented	1	2	3	4	5
The organization is capable of modifying the existing business model for AR	1	2	3	4	5
The organization supports knowledge-sharing, enables open innovation and cross-company collaboration	1	2	3	4	5
The organization invests in scalable innovation transformations	1	2	3	4	5
Accelerating innovation is part of the company culture	1	2	3	4	5
There are dedicated teams in the company to support AR across the organization	1	2	3	4	5
The organization supports management and leadership towards AR transformation activities	1	2	3	4	5
The organization’s culture towards adopting AR is continuous	1	2	3	4	5
Employees are involved in innovation processes	1	2	3	4	5
Employees are encouraged to leverage new processes or business ideas	1	2	3	4	5
The organization aligns the operator’s digital skills and qualifications to use AR	1	2	3	4	5
Employees demonstrate advanced competence in working within a digitized environment	1	2	3	4	5
The organization integrate operator needs and/or preferences in the AR development process	1	2	3	4	5
The organization actively assesses both the AR product development phase and implementation phase	1	2	3	4	5
The company uses AR technologies for work assistance by visualizing objects	1	2	3	4	5
The organization makes use of AI-based cognitive technologies like NLP, Speech recognition, Rule-based systems, etc.	1	2	3	4	5
The obtained maintenance data uses what-if analysis to build futuristic scenarios for decision support	1	2	3	4	5
General and maintenance operations are standardized in the organization	1	2	3	4	5
AR can seamlessly be integrated into maintenance procedures	1	2	3	4	5
Planning, execution, and management of processes are digitized	1	2	3	4	5
The operator uses real-time maintenance data, digitized maintenance manuals, procedures, etc.,	1	2	3	4	5
Management incorporates real-time data for planning and predicting system failure capabilities	1	2	3	4	5
The operator can auto automatically perform a fault diagnosis	1	2	3	4	5
Modern ICT, head-mounted devices, and mobile devices are utilized in maintenance operations	1	2	3	4	5
The digital platform provided to operators with the maintenance status of the rolling stock is up-to-date	1	2	3	4	5

Statement	**1 = No AR vision 5 = Integrated in organization**				
The organization has rules and regulations for using AR technologies	1	2	3	4	5
The organization established suitable AR technology standards	1	2	3	4	5
The organization manages and protects the intellectual property of AR usage	1	2	3	4	5

The semi-structured interview is presented below.

1. Who are you?
2. How are you related to AR in the organization?
3. Since when are you involved with AR technologies?
4. What are the core activities within your field of expertise?
5. Can you elaborate on the extent the organization can be considered innovative?
6. What are future goals for implementing new technologies?
7. What kind of strategy does the organization follow to implement new technologies?
8. What business model does the organization follow to implement new technologies?
9. What are the weaknesses of the integration of new technologies?
10. How would you describe the central coordination and management towards adopting new technologies?
11. Can you elaborate on the current weaknesses of maintenance operations related to digitizing the workflow?
12. How are activities currently captured in terms of maintenance and general operations procedures?
13. What is your vision for using AR for maintenance?
14. What requirements are needed before AR can be implemented in current maintenance and general operational practices?
15. How can you describe the organization’s culture towards innovation?
16. What knowledge management and sharing platforms are available?
17. Would, in your opinion, any kind of collaboration among other departments be of additional value in AR technology adaptation?
18. What is the current approach of establishing collaborative relationships with (external) stakeholders for AR adoption?
19. Are there established safety and technology standards for the utilization of AR? If so, could you provide an explanation of them?
20. Do you have any other additional thoughts/ suggestions/ ideas on this topic?

Appendix II

Stage 1: Identifying the benefits of AR in rolling stock maintenance

AR can provide maintenance operators with real-time maintenance and system failure information supporting the decision-making procedures and thereby expediting the troubleshooting process [171]. Maintenance operators are supported by a visual overlay on the physical object and given system information for step-by-step troubleshooting information. Besides this, AR facilitates remote collaboration in which maintenance operators on-site are getting guidance from experts without being physically present.

Stage 2: Feedback from experts on benefits to check the validity, clarity, and representativeness

The integration of ISM maturity modelling techniques for AR road mapping makes expert engagement integral to the problem-solving process. Moreover, integrating AR in maintenance operations requires in-depth knowledge and experience to realistically probe. There is no specific criterion on the number of experts to be engaged and the ISM approach does not require many respondents as much focus is placed on the experience and proficiency of respondents of the problem being analysed [289]. The heterogeneity of the participants should be considered, thus, this study involves experts from industry in the field of AR, rolling stock maintenance, and organizational innovations. In total, 15 experts were contacted and 11 accepted the participation invitation. The number is adequate to produce reliable findings based on their level of experience coupled with the ISM process adopted. The semi-structured interviews are based on the ISM principles which were developed into an interview guide to ensure standardized information elicited for the study. This supports checking bias and ensures uniformity in the entire process.

The requirements for the AR roadmap are identified based on Table 9.1 and expert input. The identification of the pair-wise relationships between the aforementioned components is done by experts. This process entails the experts discussing how one component influences the other and is presented in a Structured Self-Interaction Matrix (SSIM) (Figure A.II.1). The SSIM data outlines the relationships between the factors in terms of i (rows) and j (columns) and their respective relations [289]. A simple notation using the symbols: V, A, X, and O is used to denote each of the separate relationships. The data output is gathered from expert input and summarized in one matrix. The shaded area in Figure A.II.1 signifies the duplicate (j,i) references within the matrix and is ignored for this exercise.

V: Variable i will influence variable j;
A: Variable i will be influenced by variable j;
X: Variable i and variable j will be influenced by each other;
O: Variables i and j are not related and no influence exists.

Elements (j) (i)	8	7	6	5	4	3	2	1
1	X	X	A	A	X	A	A	
2	X	A	X	A	X	A		
3	A	O	A	X	A			
4	X	X	X	A				
5	V	A	A					
6	X	A						
7	V							
8								

Figure A.II.1. SSIM of maturity dimensions.

Stage 3: Establishing hierarchical levels of factors

The SSIM established direct relationships among the maturity dimensions. To check transitive relations, e.g. element 1 has a relationship with element 7 and element 7 has a relationship with element 5, then element 1 has a relationship with 5, a reachability matrix is required. To do so, the SSIM matrix is required to become a Final Reachability Matrix (FRM) binary matrix with the following conditions:

If the (i,j) entry is V, the equivalent (i,j) becomes 1 and (j,i) becomes 0;
If the (i,j) entry is A, the equivalent (i,j) becomes 0 and (j,i) becomes 1;
If the (i,j) entry is X, the equivalent (i,j) becomes 1 and (j,i) becomes 1;
If the (i,j) entry is O, the equivalent (i,j) becomes 0 and (j,i) becomes 0;

The FRM matrix with the driving and dependency powers of the maturity dimensions is presented in Figure A.II.2

Elements (j) (i)	8	7	6	5	4	3	2	1	Drivers
1	1	1	0	0	1	0	0	1	4
2	1	0	1	0	1	0	1	1	5
3	0	0	0	1	0	1	1	1	4
4	1	1	1	0	1	1	1	1	7
5	1	0	0	1	1	1	1	1	6
6	1	0	1	1	1	1	1	1	7
7	1	1	1	1	1	0	1	1	7
8	1	0	1	0	1	1	1	1	6
Dependence	7	3	5	4	7	5	7	8	

Figure A.II.2. FRM of maturity dimensions.

At this stage, the hierarchical structure and polarity between the dimensions are determined. This analysis involves the computation of the reachability set, antecedent set, and intersection set. The reachability set comprises maturity dimensions, each assigned a value of 1 (including itself) on the FRM matrix row. Correspondingly, the antecedent set consists of risk factors with a value of 1 on the FRM matrix column. The intersection set encompasses common risk factors found in both the reachability and antecedent sets. Following the hierarchical partitioning rule, maturity dimensions are categorized to a common level when reachability sets form a proper subset of the intersection set. The iterative process of partitioning involves (i) identifying the maturity dimension with identical elements in the reachability and intersection column, and (ii) removing the dimensions from the table, repeating the initial step [289]. This process continues until all maturity dimensions are appropriately labelled and partitioned. Table A.II.1 illustrates the step-by-step iterative level partitioning procedure.

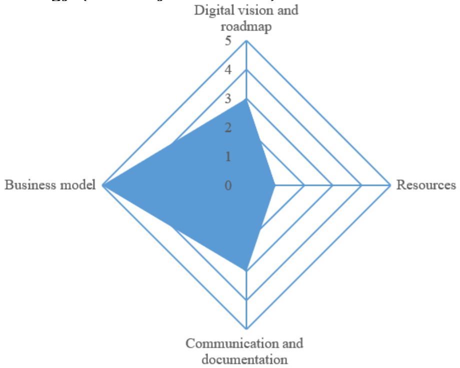
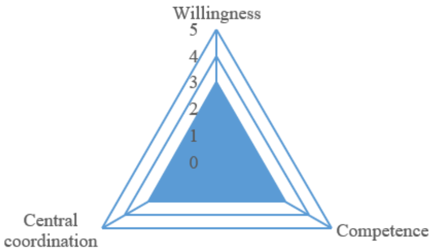
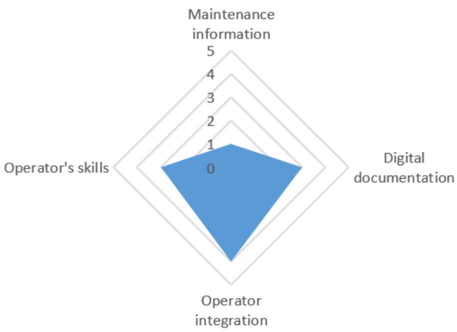
Table A.II.1. Level partitioning procedure.

Maturity dimension	**Reachability set**	**Antecedent set**	**Intersection set**	**level**
Level 1				
1	1, 4, 6, 7, 8	1, 2, 3, 4, 5, 6, 7, 8	1, 4, 6, 7, 8	I
2	1, 2, 4, 6, 8	2, 3, 4, 5, 6, 7, 8	2, 3, 6, 8	I
3	1, 2, 3, 5	3, 4, 5, 6, 8	3, 5	
4	1, 2, 3, 4, 6, 7, 8	1, 2, 4, 5, 6, 7, 8	1, 2, 4, 7, 8	I
5	1, 2, 3, 4, 5, 8	3, 5, 6, 7	3, 5	
6	1, 2, 3, 4, 5, 6, 8	2, 4, 6, 7, 8	2, 4, 6, 8	
7	1, 2, 4, 5, 6, 7, 8	1, 4, 7	1, 4, 7	
8	1, 2, 3, 4, 6, 8	1, 2, 4, 5, 6, 7, 8	1, 2, 4, 8	I
Level 2				
3	3, 5	3, 4, 5, 6, 8	3, 5	
5	3, 5	3, 5, 6, 8	3, 5	
6	2, 4, 6, 8	2, 4, 6, 7, 8	2, 4, 5, 8	II
7	1, 4, 7	1, 4, 7	1, 4, 7	II
Level 3				
3	3, 5	3	3	III
5	3, 5	5	5	III

Appendix III

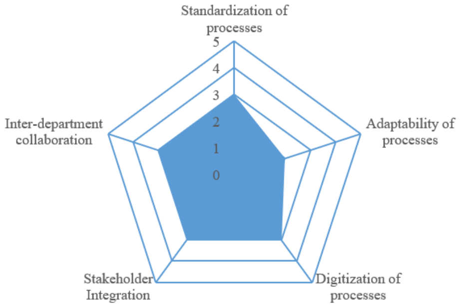
Table A.III.1 presents detailed information concluded from the semi-structured interviews. Each maturity dimension presents its radar chart with measurement items.

Table A.III.1. Semi-structured interview results measurement items.

<table>
<tr><th>Radar chart for each maturity and readiness dimension
Online questionnaire results</th><th>Motivation
Semi-structured interview summary</th></tr>
<tr><td>Strategy (maturity score: 2.9)

</td><td>An AR roadmap is developed by the technical department of the organization, however, no comprehensive roadmap is available company-wide. There is a need for dedicated teams/platforms in charge of AR-specific work supported by centralized online maintenance and operational documentation. Resources have been made available for AR-related innovations. Currently, the organization exploits AR technology push influencing the maintenance strategy.</td></tr>
<tr><td>Leadership (maturity score: 2.8)

</td><td>Management does not have sufficient and in-depth AR knowledge making communication and knowledge management difficult. Having strong leadership and guidance in the AR domain supports innovations and leadership development is strongly recommended.</td></tr>
<tr><td>Maintenance operations (maturity score: 2.8)

</td><td>Real-time monitoring data is not available for direct analysis and historical maintenance data is not always up-to-date and accessible. Current maintenance procedures are supported with tablets and online documentation. The organization aims to have AI/AR predictive maintenance in the future. The organization aims to prioritize the ease of use of new technologies.</td></tr>
</table>

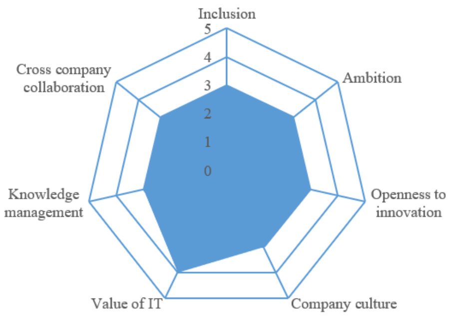
Radar chart for each maturity and readiness dimension *Online questionnaire results*	Motivation *Semi-structured interview summary*

General operations (maturity score: 2.7)



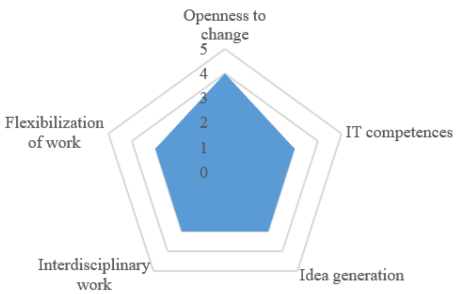
The organization identifies itself as bureaucratic where processes are difficult to change and require high-level management support. The organization invests in digitization by utilizing 3D data. Operations follow different departmental procedures and inter-department collaboration is not yet viable.

Culture (maturity score: 3.0)



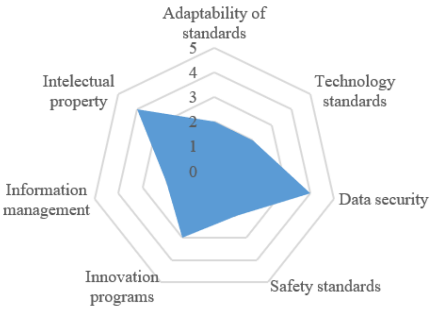
The organization has high innovation ambitions, however, motivating employees can be challenging. Showing the technology potential, and capturing, and sharing knowledge supports employees. Employees see the organization as innovative supporting end-user solutions and allowing testing of new technologies and products. Challenges are faced in the IT infrastructure for AR usage e.g. programming.

People (maturity score: 3.4)

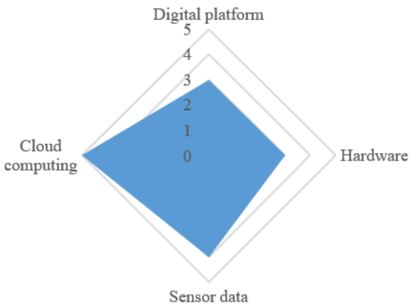


Employees see the importance of innovation and expect benefits related to maintenance efficiency, quality, and problem-solving. The improvement relates to generating new ideas, testing technology products, and developing technologies. Employees are willing to invest time and effort in technology evolvements, however, the workload cannot be exceeded.

<table>
<tr><th>Radar chart for each maturity and readiness dimension
Online questionnaire results</th><th>Motivation
Semi-structured interview summary</th></tr>
<tr><td>Governance (maturity score: 2.6)



</td><td>General standards are not expected to be adapted significantly. New AR-related standards are to be created and documented related to cyber security, safety, hardware, intellectual property, and privacy standards.</td></tr>
<tr><td>Technology (maturity score: 3.6)



</td><td>The organization has a modern IT department and maintenance procedures are supported by sensor equipment for data logging. Operators use tablets for maintenance support. A variety of AR technologies are examined for maintenance operations and pilot programs are developed.</td></tr>
</table>

Chapter 12 – References

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