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

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Abstract

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 train design, information technology systems and operational technology systems converge, resulting in complex train failures, maintenance procedures, and activities. Troubleshooting train 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. Augmented reality (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. Laboratory testing is used as input for future design building blocks.

Keywords: Augmented Reality; Decision-support system; Maintenance;

1. 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 [1]. Besides this, maintenance procedures are becoming data-driven and analysis of failures is even more complex due to the convergence of information technology (IT) and operational technology (OT) systems [2]. 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 [3][4]. 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 [5].

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 [6]. New technologies, such as Artificial Intelligence (AI), Augmented Reality (AR), and Internet of Things (IoT), are now utilized in the decision-making process. Because it is difficult to understand complex

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failures, new technologies supporting the decision-making process are thriving to help operators understand train systems and their failure behavior 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 [6].

Given the increasing complexity of IT/OT train 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 [5]. 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 [8]. 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 [8].

Altogether, AR brings real-life IT/OT system conditions into focus by visualizing information to better understand train failures and ultimately speed up the decision-making process for operators [9]. 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.

2. 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 [8].

An example of AR decision-making is given in the embedded electronic field for training maintenance professionals [10]. 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 [11]. 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 [12]. 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 is 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 [5]. 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 an AR decision-making support tools [13].

The novelty of this research focuses on the combination of ways to filter, select, and translate data into understandable information for the operator, captures 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 train 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 1. AR plays an important role in the highlighted boxes.

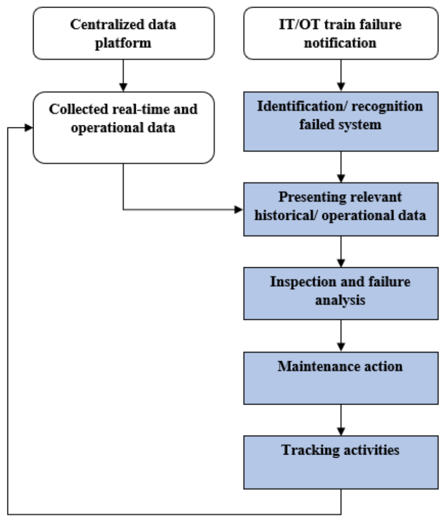

Figure 1. Schematic overview of AR decision-making tool.

3. 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. In total, 14 troubleshooting experts are available to participate in the research.

3.1 Interview and workshop sessions setup

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. 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. 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. 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, 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. The results are shared and discussed with the interviewee afterwards. To systematically process the unstructured data, ATLAS.ti is used [14]. Data analysis is based on open coding procedures in which codes are developed and modified during the coding process.

3.2 Case study setup

A real-life train 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 train series, built between 1994 and 2009 and refurbished starting in 2015 [16].

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 2 represents the flowchart of the AR decision-making tool. AR will play a significant role in consequently visualizing, guiding, assisting operators in their decision-making, and tracking the maintenance activities.

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, basic implications of the what-if analysis is 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 includes each maintenance task executed by the operator. An integration connects the train 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. 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.

4.1 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 presents 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 sector. Malfunctioning of the CAN system causes the train 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 train operations.

Operators state that sanitary failures are often not resolved correctly, causing an accumulation of system failures and forcing the train 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.

4.1 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.

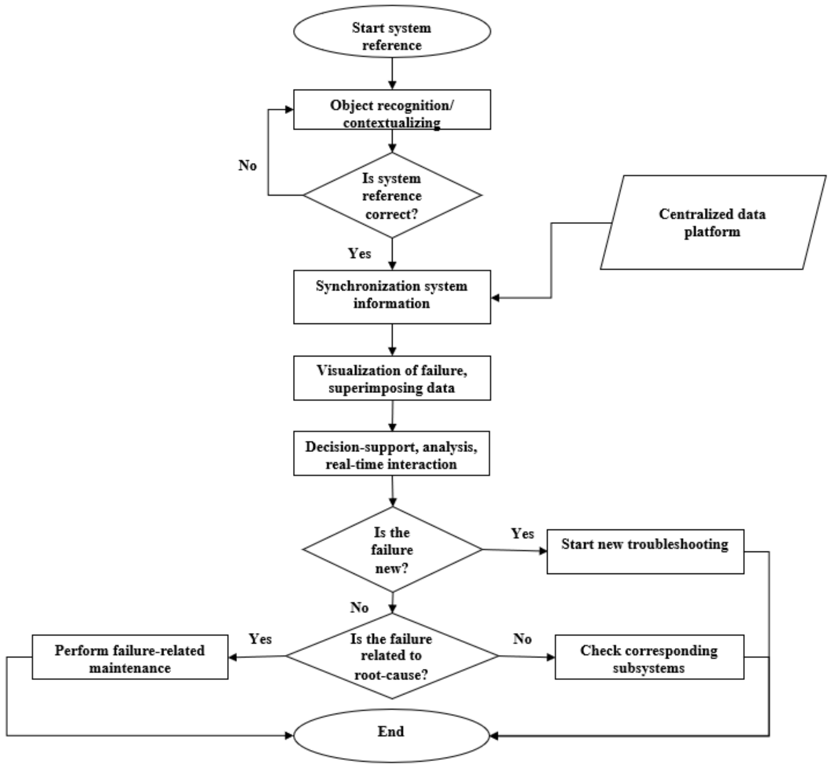

Figure 2. Flowchart of the AR decision-making tool.

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 is 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 User Interface design is developed in game design software Unity and visualizations are presented in the Microsoft HoloLens 2.

5. 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 train data, such as real-time system data and maintenance data (see figure 2). 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 train and connected in the laboratory for simulation purposes. To simulate this failure notification, all relevant failure sensor data is collected from the train and displayed in a laboratory environment.

5.1 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 3.

Troubleshooting train 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

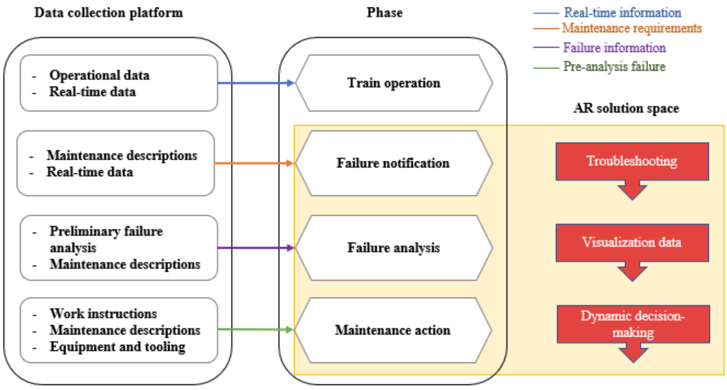

Figure 3. Centralized data platform.

focuses on a specific train 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 the 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.

5.2 Initializing AR decision-making tool

The given error code regarding the bioreactor of the sanitary system generates multiple diagnoses and corresponding maintenance actions. Table 1 presents the percentage of occurrence of the failure code for each diagnosis.

Table 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.

5.3 AR decision-making tool setup

The HoloLens 2 is used as an end tool to recognize the object, present maintenance solution 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 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 the 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.

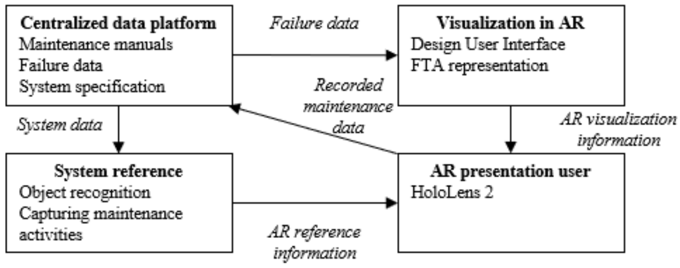

Figure 4. Setup AR decision-making demonstrator.

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 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.

6. Results

The AR decision-making tool consists of multiple steps which are represented in figure 5. 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 1). From this, associated maintenance actions are presented.

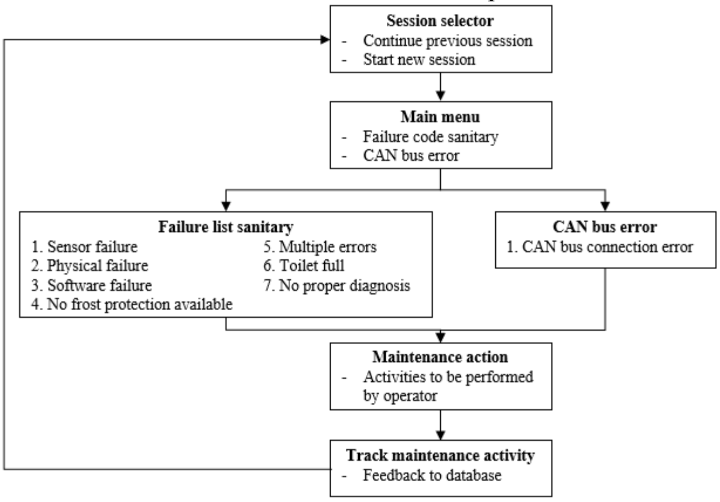

Figure 5. AR decision-making tool sanitary system VIRM.

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.

7. Conclusions and future work

This paper 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 train 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 analyze the limitations of the current laboratory setting.

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