Whitepaper

Safety Considerations for Use of Artificial Intelligence in Train Maintenance

Partial Automation of Visual Inspection Tasks

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Abstract

Even though the effectiveness of artificial intelligence in railway maintenance is indisputable, safety concerns still cause a restraint to enable widespread application. Together with experts from the railway system safety and artificial intelligence domain as well as research institutes, DB Fernverkehr AG develops applicable artificial intelligence safety requirements within the Autonomous Inspection of Rolling Stock (ARGO) project to allow for compliance with railway safety standards in the European Union. The safety argumentation is based on DIN EN 17023 and Implementing Regulation (EU) No 402/2013. The safety argumentation within this project follows the tree-shaped goal structuring notation from the safety-critical systems club. For each artificial intelligence cluster from the project hazard log, a dedicated safety argumentation tree is developed. The safety measures that are represented by the leaves of these trees need to be fulfilled to allow for operational use.

Keywords: SafeAI; AI Act; Railway; Train Maintenance; CSM-RA; Visual Train Inspection

1. Introduction

As part of high-speed train maintenance, visual inspection tasks are currently performed by qualified maintenance personnel based on a maximum distance driven limit. The corresponding process is time consuming and requires lots of manual work. Hence, DB Fernverkehr AG aims to partially automate this process within the ARGO project as part of the Europe's Rail FP3-IAM4Rail funding program [1]. The project aims to develop a system that uses optical sensors to identify defects in the outer train shell and on the bogie. A successful implementation of the project could lead to reduced way times in maintenance and an increased occupational safety for maintenance personnel.

While the detection of dimensional deviations from the nominal state is typically solved via classical computer vision approaches, the identification of impermissible dents, cracks, tears, or discoloration of components is a more challenging task. One possible approach is the use of machine learning anomaly detection techniques such as (Variational) Autoencoders or certain types of Generative Adversarial Networks that create an anomaly score based on a reconstruction error. The use of such deep learning techniques in safety relevant applications must meet regulatory requirements for changes in train maintenance. DIN EN 17023 [2] on the creation and modification of maintenance plans must be considered within the ARGO project due to the application of innovative methods and a change of the concept of maintenance within the current train maintenance plan. Regarding the risk management process, DIN EN 17023 refers to Implementing Regulation (EU) No 402/2013 on the common safety method for risk evaluation and assessment [3], which controls how safety assurance for safety relevant changes in the railway system can be achieved. Therefore, Implementing Regulation (EU) No 402/2013 is the basis for the development of SafeAI in train maintenance.

The following sections provide a framework of AI-related safety requirements developed within the FP3-IAM4Rail funding program. These requirements need to be addressed when developing and maintaining SafeAI for maintenance purposes. Section 2 provides an overview about Implementing Regulation (EU) No 402/2013. Based on the structure of this implementing regulation, the functionality of the ARGO vehicle as well as solution strategy for defect detection is described in Section 3.1. Afterwards, the process of hazard identification and classification for the ARGO project is outlined in Section 3.2. Section 3.3 provides applicable risk acceptance principles for the ARGO project and outlines the challenges linked to the safety assurance process. Section 4 concludes.

2. Implementing regulation (EU) 402/2013

2.1. System Definition

The system definition is the first step within the risk assessment process. It serves as the basis for the identification and control of hazards. The system definition comprises the definition of the system objective, system functions and elements, system boundaries and interacting systems as well as a description of the system environment.

2.2. Hazard Identification and Classification

The proposer of the risk assessment process shall systematically identify reasonably foreseeable hazards for the whole system under assessment, its functions where appropriate and its interfaces. For this purpose, the proposer shall use wide-ranging expertise from a competent team. All identified hazards shall be registered in the hazard log. Whenever a hazard cannot be classified as broadly acceptable risk, a selection of a risk acceptance principle must be performed to control possible hazards.

2.3. Risk Acceptance Principle

The risk acceptability of the system under assessment shall be evaluated by using one or more of the following risk acceptance principles: the application of code of practice, use of a reference system or an explicit risk estimation. The application of these risk acceptance principles shall identify possible safety measures that make the risk(s) of the system under assessment acceptable. Among these safety measures, those selected to control the risks shall become the safety requirements to be fulfilled by the system.

2.4. Demonstration of Compliance with Safety Requirements

Prior to the safety acceptance of the change, fulfilment of the safety requirements resulting from the risk assessment phase shall be demonstrated under the supervision of the proposer. Any inadequacy of safety measures expected to fulfil the safety requirements, or any hazards discovered during the demonstration of compliance with the safety requirements shall lead to reassessment and evaluation of the associated risks by the proposer.

3. Safety assurance in Artificial Intelligence

One of the major challenges within the ARGO project is the proof of safety assurance for subsystems which implement AI models. Representative challenges linked to the safety assurance in AI are explained in the following sections and follow the structure of Section 4.

3.1. Introduction to ARGO System Definition[1]

The Underfloor Inspection Vehicle is a robot capable of performing visual underfloor inspection on maintenance and siding tracks. After one year of development, the vendor was able to deliver a first prototype for validation. The prototype is depicted in Figure 1. The robot is equipped with five cameras for surroundings monitoring and data acquisition. One of the cameras is mounted on a 360° rotatable and 180° tiltable robot arm. The robot can be controlled remotely via a tablet. The validation of the robots moving capabilities took place in different maintenance shops and on different trains. The revised version for full automation of inspection trips and image recordings is currently under development.

Figure 1: ARGO Vehicle for Underfloor Inspection

For future development, DB Fernverkehr AG aims to integrate the ARGO system into its train maintenance processes. One major challenge is the automated analysis of the recorded images. A possible approach to detect defects in maintenance via machine learning is the use of anomaly detection methods. Anomalies are data points that stand out from other data points in the data set and do not conform the normal behaviour in the data. Anomaly detection is especially useful for the described use case due to the highly imbalanced data encountered in train maintenance. Most of the inspection data does not show any defects. Hence, collecting and labeling sufficient anomaly data would be infeasible.

Most existing representation-based approaches extract normal image features with a deep convolutional neural network and characterise the corresponding distribution through non-parametric distribution estimation methods. The anomaly score is calculated by measuring the distance between the feature of the test image and the

[1] The presented content does not replace a comprehensive system definition as required by Implementing Regulation (EU) No 402/2013 2.1.2

estimated distribution. An example of a torn electrical connection with a high anomaly score is shown in Figure 2. Notable examples for anomaly detectors that apply deep learning methods include (Variational) Autoencoders, Generative Adversarial Networks, One-Class Support Vector Machines and Deep Belief Networks.

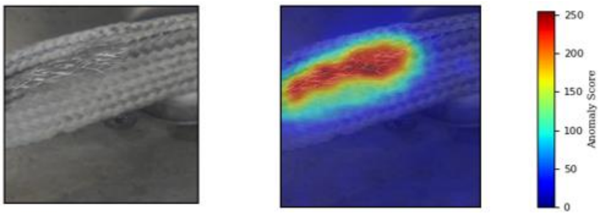

Figure 2: Anomaly Score of a torn Electrical Connection.

3.2. Development Process for the Hazard Log

In a first step, potential hazards of system, operational and organisational failures are identified based on a system definition that is developed in an iterative manner. The identification of hazards is based on expert knowledge from experts within and outside the railway domain. Potential consequences of these hazards are identified, and their risk level is assessed based on risk acceptance categories from DIN EN 50126-1 [4]. Whenever the risk level is not acceptable, hazards related to AI are considered within safety relevant AI clusters. The associated clusters consist of requirements for the software development life cycle, model development, dataset quality, synthetic data, image coverage, image quality, labeling, testing, information overflow, shadow experiment, deployment strategy and monitoring. Within these clusters, safety requirements are derived via the Goal Structuring Notation (GSN) (see [5] for explanation) as exemplified in Figure 3.

The vendor must demonstrate compliance with these safety requirements. An excerpt of these requirements is presented in the following sections.

3.3. Risk acceptance Principles for Safety Assurance in ARGO Project

As described in Section 2, Implementing Regulation (EU) No 402/2013 distinguishes between the use of code of practice, application of a reference system and explicit risk estimation as risk acceptance principles. These principles are described in the following.

3.3.1. Code of Practice for Automated Visual Inspection

To present the results for the application of code of practice within ARGO, this paper differentiates between a Conventional Software Development Lifecycle (SDLC) and the Model Development Lifecycle (MDLC).

3.3.1.1 Software Development Lifecycle

Due to the consideration of safety relevant software components within the ARGO project, DB Fernverkehr AG sets high standards for the SDLC. Without a standardised SDLC that is coordinated between DB Fernverkehr AG and the vendor, the prerequisites for a safe integration into railways system might be insufficient and systematic software bugs could occur. Therefore, the following paragraphs describe requirements for the safety assurance process to enable automated analysis for underfloor inspection.

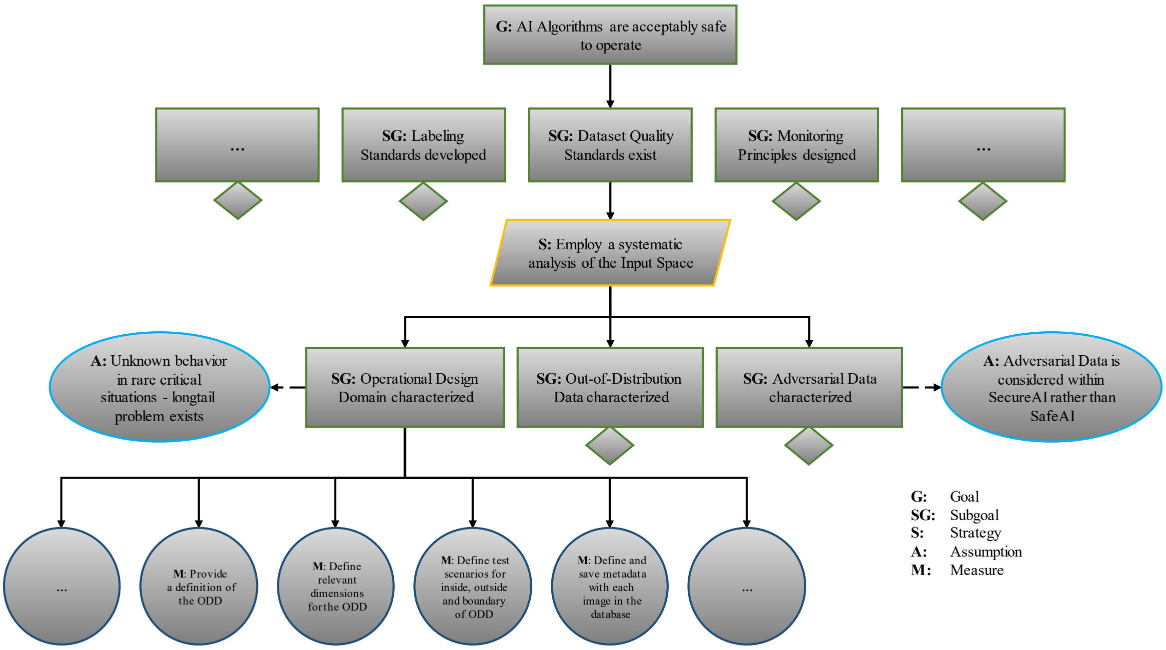

Figure 3: GSN Characterisation Operational Design Domain

One possible approach for a standardised SDLC is the use of DIN EN ISO 13849-1 [6] which is harmonised under the Machinery Directive 2006/42/EC [7] and its future successor, the Machinery Regulation (EU) 2023/1230 [8]. DIN EN ISO 13849-1 is designed to demonstrate the safety of machinery for safety-related parts of control systems. Depending on the specified Performance Level (PL), various conditions for embedded and application software must be fulfilled. For the ARGO project at DB Fernverkehr AG, the documented requirements in this norm are too unspecific to address the complexity of the ARGO project.

A possible alternative to DIN EN ISO 13849-1 is the application of DIN EN 50716 [9]. Whenever software for programmable electronic systems for use in control, command for signalling applications or on-board rolling stock is developed, the requirements from DIN EN 50716 must be considered. Published in September 2024, DIN EN 50716 replaces DIN EN 50128 and DIN EN 50657 whose implemented requirements are considered as compliant for pre-existing software.

The ARGO system is neither a signalling nor an on-board rolling stock system. Yet, the safety department of DB Fernverkehr AG regards the innovative ARGO project as comparable. This is because the maintenance system can be considered as a discrete train sensor that checks the system integrity of safety relevant components in fixed distance driven intervals. Therefore, safety requirements for the development of such an automated analysis system should be based on this standard. A prerequisite for defining relevant software requirements is the classification of the safety integrity levels (SIL). The SIL can be considered as the probability of a safety instrumented function (SIF) satisfactorily performing the required safety functions under all stated conditions within a stated period. Different methods to perform their classification can be found in IEC 61508-5 [10], DIN VDE V 0831-103 [11] or Sicherheitsregelung Fahrzeuge (SIRF) of the German Federal Railway Authority [12]. The requirements stated in DIN EN 50716 depend on SIL and compromise required document types for the SDLC as well as techniques and measures to be applied in safe software development, i.e. defensive programming, modular approach, design and coding standards and performance testing. The vendor is responsible to follow all SIL dependent requirements that are labeled as “mandatory” and must argue whenever requirements labeled as “highly recommended” are not implemented. Moreover, an independent assessor must assess the compliance of the SDLC with DIN EN 50716.

3.3.1.2 Model Development Lifecycle (MDLC)

Regarding the application of code of practice for AI models, DB Fernverkehr AG collaborated with a research institute [13] to investigate state-of-the-art rulebooks applicable for safety assurance for machine learning image processing. The analysis included the investigation of domain independent rulebooks as well as domain dependent rulebooks from the automotive, medical, aviation and rail sector. Furthermore, current applications of machine learning in safety-relevant areas were outlined by the research institute. The outcome of this research analysis suggests that many rulebooks are currently under development and published rulebooks tend to address certain topics from within the assurance lifecycle but do not provide a comprehensive safety assurance framework for the ARGO project.

The most prominent example of rulebooks is the European AI Act [14] which came into enforcement by the European Parliament in August 2024. Beyond the risk-based categorisation to follow a set of obligations within the legal framework, the AI Act itself does not provide sufficient technical details useful for the AI safety assurance within ARGO. At the time of this writing, there is no final agreement on whether the ARGO system must be considered a high-risk AI system or a limited risk AI system. Regardless of the classification, requirements for providers of high-risk AI systems are already part of the safety requirements from the hazard log in accordance with Implementing Regulation (EU) No 402/2013. This finding shows the already existing linkage between Implementing Regulation (EU) No 402/2013 and the AI Act in the railway domain.

3.3.2. Reference System for Automated Visual Inspection

At the time of this writing, there is no known reference system comparable to the ARGO system that aims to replace visual inspection on the outer train shell and on the bogie. A system with similar functions and interfaces as well as similar operational and environmental conditions with long-term in-use experience is not known to the authors. Yet, systems for maintenance assistance instead of replacing systems that pursue a similar goal are already in place. One example is the VR FleetCare Scanner [15] that uses lidar scanners and cameras to detect loose bolts, leakages, open hatches, or broken springs. Another example is a specially dedicated train from Schweizerische Bundesbahnen (SBB) instrumented with cameras to detect rail defects by using AI [16]. However, the system's reliability has not been proven to an extent that allows for trustworthiness to replace manual inspection entirely.

3.3.3. Explicit Risk Estimation for Automated Visual Inspection

Due to the lack of directly applicable rulebooks as well as a reference system for the ARGO system, our work focused on a systematic development of safety requirements to allow for hazard control via explicit risk estimation. The safety requirements were developed together with a research institute [13] in a GSN structure (see [5]) and further developed by studying publications from the SafeAI research sector. The proposed safety requirements were discussed within a DB SafeAI expert group and represent a minimum set of safety requirements to be addressed when developing safety related applications within DB Fernverkehr AG.

The following subsections present excerpts of clusters of safety requirements that need to be considered when developing safety related models for the ARGO project. Please note that the presented clusters only depict a subset of requirements. For a more comprehensive version we would like to reference to the developed but unpublished GSN trees.

3.3.3.1 General AI Safety Requirements

In accordance with the AI Act, safety requirements for the ARGO projects encompass high standards for data governance, technical documentation, record-keeping, and instructions for use. These topics are relevant for all identified clusters.

Data governance defines requirements for training, validation, and testing data. A prominent example of insufficient data governance is data leakage. In data leakage, knowledge of the hold-out test set leaks into the training set. This could lead to an overestimation of the model performance which in turn could lead to safety-critical predictions on new data.

A comprehensive technical documentation as well as record-keeping allows for traceability and reproducibility of results or improvements for future revisions. Furthermore, it includes a concept for change management.

Instructions for use of the AI system can help downstream deployers to better understand the system and allow for human oversight.

3.3.3.2 Shadow Experiment

The basic principle Globalment au Moins Equivalent (GAME) from DIN EN 50126-2 states that any newly introduced public transport system/subsystem or any modification to an existing system/subsystem should be as safe (or safer) than the existing system recognised as the reference system.

To follow the GAME principle, a shadow experiment is set up to compare failure probabilities in the detection of defects between human versus machines. The design is such that for a specified and reasoned time interval, the ARGO system and the human worker perform the same inspection tasks simultaneously. For this time interval, environmental and boundary conditions must be defined. Yet, it is questionable how the results between human and machine can be compared. One could argue that False Negatives (FN) by the automation system can be compensated by True Positives (TP) of the ARGO system when the worker classification turns out to be wrong (FN) in a comparison to a defined ground truth. Additionally, one could argue that a compensation would only be allowed for functions with the same SIL. The design of potential compensation methods for FNs of the automation system needs to be addressed in future research.

From an empirical perspective, it is challenging to quantify the true human performance in railway maintenance. Current research addressing human performance can only be used to a limited extent for the railway system network. Von Hinzen [17] determined theoretical values for the probability of human induced errors depending on the load situation of the worker and the type of action. This approach was further developed in Hammerl's dissertation [18] to model a new, tabular model of human behavioural possibilities, considering the work systems of train drivers and dispatchers as well as their interaction. The investigation of human performance perceptions in terms of sensory perception and information processing capability is also part of the ATO-SENSE project [19], in which the requirements for an Automatic Train Operation (ATO) system are to be derived from human performance. The results can be the starting point for the evaluation of the safety of the system.

3.3.3.3 Operational Design Domain

To define the dimensionality of the input space in artificial intelligence, the Autonomous Driving System (ADS) sector has introduced the term Operational Design Domain (ODD). SAE J3016 [21] defines the ODD as the "[…] operating conditions under which a given driving automation system, or feature thereof, is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics". The top-level attributes differentiate between scenery, environmental conditions, and dynamic elements. For these top-level attributes influencing sub-attributes including their range of values are defined. This approach from the automotive sector can be transferred to the railway sector. However, when considering that the number of all possible tests in pairwise testing is $\prod n_i$ given a test case with N parameters $\{P_i\} = \{P_1, P_2, \dots, P_N\}$, the range of parameters as $R(P_i) = R_i$ and $|R_i| = n_i$, the effort for validation activities grows exponentially. Due to the exponential growth of the number of combinations, practical experiments alone would be too costly. An alternative is the application of scenario-based tests. The underlying models must approximate reality to meet the goals for a predefined simulation-to-reality-gap. Also, the test space can be reduced by reduction techniques such as Pairwise Independent Combinatorial Testing (PICT). Within PICT, a test set is created such that all t-wise combinations appear at least once in the test set (t = 2 for interactions between two attributes). Case studies have shown that many failures result from a single characteristic failure or a combination of two characteristics [22].

3.3.3.4 Synthetic Data

Synthetic data is artificially generated data that simulates real data. Synthetic data is particularly useful when real data is rare or difficult to collect (imbalanced data). The advantage of synthetic data is that large quantities can be used to create diverse data sets that can be used to train machine learning models. Unsupervised learning variational auto-encoders, generative adversarial networks or diffusion models can be used to generate synthetic image data. These methods for generating computer-generated methods can be supplemented by computer-based or physical methods. Computer-based approaches include augmentation using graphics editors. Physical methods include the attachment of foreign objects or the deliberate creation of damage. Within the ARGO project, real data of breakages is scarce. Yet, most safety-critical events appear in scenarios of low occurrence probability (see [23] for a description of the long-tail problem). Therefore, the creation of synthetic datasets is essential for V&V activities of developed algorithms within the ARGO project.

It is crucial to test synthetic data for conformity with real data, which is expressed by the simulation-to-reality gap. For this purpose, visual inspections by qualified personnel should be complemented by computational approaches such as image similarity metrics, metrics for perceptual quality and forensic classifiers. Moreover, conformity with the labeling guide (see section 3.3.3.5 on labeling) should be assessed. Synthetic data is labeled implicitly during its creation but does not necessarily follow the same labeling process for real data. Nevertheless, it must be ensured that all data is labeled consistently. If synthetic data is used for testing and training, different techniques for generating synthetic data should be used for training than for the test data. Otherwise, this could lead to overfitting regarding synthetic data and accordingly result in the test data not necessarily being generalisable and therefore not representative of real data. This would be an example of a specific form of data leakage.

3.3.3.5 Labeling Quality

In machine learning, the term labeling refers to the process of labeling or annotating data points to capture information about the observable content or category of the respective data point. As such, labels are intended to represent the true, observable attributes that can be compared with attributes predicted by models.

In safety related applications, crowdsourcing for labeling can only be performed when the qualification of the labeler is considered, i.e., most internet users would not be suitable candidates to assess the integrity of safety related train components. Within the ARGO project, qualified maintenance personnel will be responsible for the labeling based on a standardised labeling guide. The labeling guide will include labeling rules, the presentation of examples and processes for the extension and the update of the labeling guide.

To test for consistency between labelers, an assessment of interrater reliability metrics such as Cohens Kappa or Krippendorfs Alpha could take place [24]. A low interrater reliability could require rework of the labeling guide, advanced training, or higher requirements regarding the qualification of the labeler.

Also, labelers classifying defects should not have to decide dichotomously as this could lead to forced decisions. Instead, an "uncertain" label should be included. Yet, a high number of such labels could indicate insufficient labeling rules or insufficiently trained labeling personnel.

4. Conclusion

The ARGO project aims to partially automate the visual inspection of German high-speed trains. Due to the safety-relevance of the inspection tasks, DIN EN 17023 and Implementing Regulation (EU) No 402/2013 must be considered. Based on this Implementing Regulation, a risk management system is established throughout the AI system's lifecycle. Current rulebooks applicable for the railway domain are insufficient to cover all AI related risks from the hazard log. Therefore, DB Fernverkehr AG decided to develop safety requirements relevant for the AI system's lifecycle that need to be considered in the automated image analysis. The development was accompanied by experts from the system safety and AI domain as well as state-of-the-art research.

Safety requirements were derived from high level safety goals through the Goal Structuring Notation. For the operational integration of the ARGO system in the visual inspection tasks, these safety requirements serve as a framework to create SafeAI for maintenance of high-speed trains.

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