Using Mixed Reality for Safety-Critical Testing in Railway Systems

Raphael Kling, Manuel Wild, Marvin Wieschollek, Martin Cichon

Karlsruhe Institute of Technology - Institute of Vehicle System Technology, 76131 Karlsruhe Rintheimer Querallee 2, e-mail: {raphael.kling, manuel.wild, marvin.wieschollek, martin.cichon}@kit.edu

Abstract *– Rail transport is essential for meeting climate goals, but challenges such as congestion, high costs, staff shortages, and low predictability limit efficiency. Automated Train Operation can improve availability and reduce costs, yet the development requires extensive safety validation. Field testing is limited by infrastructure constraints, operational disruptions, and the rarity of hazardous scenarios. This paper proposes a Mixed-Reality-based validation approach that injects virtual sensor data into real-world sensor streams, enabling safe and realistic testing of rare and safety-critical situations. The method enhances field-test value, improves validation completeness, and helps bridge the simulation-to-reality gap for automated rail systems.*

Keywords: *Vehicle In the Loop, Augmentation, Scaled Testing, Automated Train Operation*

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Introduction

Rail transportation is one of the safest modes of transport due to strict regulatory requirements and comprehensive validation of safety-critical systems. However, railway operators face increasing challenges, including growing traffic demand, limited network capacity, and a demographic shift that is leading to a shortage of qualified operational staff. Automated Train Operation (ATO) is therefore considered a key technology for improving operational efficiency, availability, and capacity utilization. While ATO is already established in metro systems and isolated industrial railways (Rossberg 2008; Rio Tinto 2017), its deployment in open railway networks remains challenging.

On-sight operations including shunting are particularly demanding because trains often operate without signal protection. Continuous observation of the environment is required, including the detection of obstacles, assessment of switch positions and track conditions, and the corresponding adaptation of train movements. For automation, these perception- and decision-making responsibilities must be transferred to the automated system. For higher Grades of Automation (GoA), the system must therefore be capable of perceiving, interpreting, and responding to dynamic environmental conditions while ensuring safe operation (IEC 2014).

The validation of such perception-driven systems requires extensive testing under a wide range of operational conditions. Although field testing provides realistic results, it is costly, difficult to scale, and often unacceptable for hazardous scenarios. Simulation offers a safe, repeatable, and cost-effective alternative, but purely virtual environments are limited by the simulation-to-reality gap (Manivasagam et al. 2023). To address these challenges, this paper presents a Mixed Reality (MR) approach for railway applications that combines simulation and field testing by augmenting real sensor streams with virtual sensor data. By synchronizing real and virtual environments, the approach enables safe and realistic testing of safety-critical railway scenarios while reducing the limitations of both purely simulated and purely real-world testing. To enable faster development of this approach without relying on field testing, scaled testing is used for development (Hofmeier and Cichon 2025a).

State of the Art and Research Gap

The validation of highly automated vehicles is increasingly shifting from mileage-based testing toward scenario-based methodologies, as rare safety-critical events cannot be efficiently covered through real-world operation alone (Bagschick et. al. 2018). To achieve systematic and traceable validation, the Operational Design Domain (ODD) defines the conditions under which the System under Test (SuT) is expected to operate safely, while scenario-based methods derive representative test cases from these conditions (SAE International 2021).

To evaluate such scenarios, Software-in-the-Loop, Hardware-in-the-Loop, and Vehicle-in-the-Loop progressively integrate real-world components into simulation environments (Park, Chung, and Lee 2020). These approaches enable efficient, repeatable, and increasingly realistic testing of scenario-based test cases. However, they remain limited in accurately capturing the interaction between perception systems and real operating conditions. At the same time, purely field-based validation is often impractical, as hazardous and safety-critical scenarios occur only rarely and cannot or are unacceptable to be reproduced on demand. While the automotive domain benefits from reusable and sensor-realistic ADAS test dummies, comparable solutions are difficult to implement in railway environments because trains are constrained to fixed tracks. Consequently, a gap remains between scalable simulation-based testing and realistic field validation, highlighting the need for alternative validation approaches.

To address this gap, this paper presents a MR validation framework for railway environments that integrates virtual sensor data into real sensor data. The implementation is based on Vir2Rail (Hofmeier 2026), the approach combines the scalability and repeatability of simulation with the realism of field testing, enabling the validation of safety-critical railway scenarios while reducing the simulation-to-reality gap.

Methodology

This chapter introduces the general approach of this method. The objective is to create synthetic sensor measurements that are indistinguishable from those produced by physical objects, enabling safe testing of safety-critical scenarios while preserving the realism of the surrounding environment. By combining real and virtual elements, the approach reduces the simulation-to-reality gap and supports realistic validation under controlled conditions. Although demonstrated using LiDAR and RGB camera, the concept is transferable to other sensor modalities, including radar and ultrasonic sensors. Successful implementation requires compatible virtual object representations and continuous spatiotemporal synchronization between real and virtual worlds.

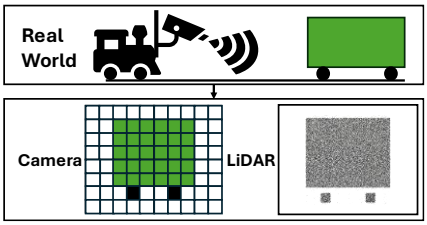


Figure 1 Real-World Sensor Data Generation Process

Figure 1 illustrates the sensor data generation process in a railway scenario when approaching a wagon. An RGB camera records image data as pixel arrays influenced by optical and sensor characteristics, while LiDAR generates point clouds representing distance measurements derived from reflected laser signals.

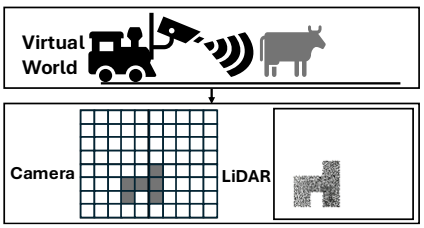


Figure 2 Virtual Sensor Data Generation Process

Figure 2 shows the process for virtual sensor data generation. The virtual train with similar sensor setup as in Figure 1 is approaching the virtual obstacle to be augmented, in this case a cow.

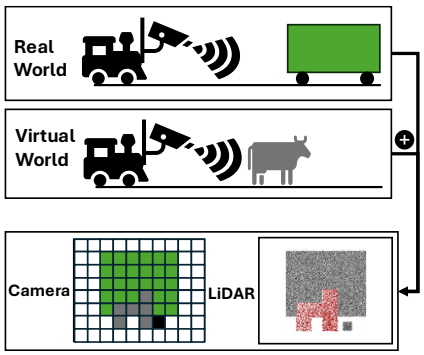


Figure 3 Fused Sensor Data

Figure 3 illustrates the fusion of real sensor data with virtual objects. In this example, a virtual cow is inserted into the sensor stream of a train approaching a wagon. For the LiDAR, the wagon is shown in black, while the virtual cow is represented by red points. Pixels belonging to the virtual cow replace the corresponding wagon pixels while virtual points from the LiDAR overwrite real points, enabled by the availability of pixel- and point-wise ground-truth annotations in virtual sensor data. By aligning real and virtual train trajectories and using realistic sensor models, virtual obstacles can be accurately positioned within real data streams.

The central hypothesis is that perception systems respond to virtual obstacles in the same way as real ones. To validate this, datasets with real and augmented objects within the same scenery will be created and evaluated. This enables testing the reaction of already existing object detectors.

Implementation

To reduce cost and increase availability while supporting fast adaptation and transferability of the results to full-scale applications at first a 1:32 scaled environment is used which is combined with a digital twin, the setup is similar to (Hofmeier and Cichon 2025b). After successful implementation in 1:32 scale the transformation to full scale is shown.

Creating Virtual Sensor Data

To ensure realism, both the geometric perspective between sensor and environment and the underlying sensing principles must be accurately represented and match between the virtual and the real-world.

Correct perspective is achieved by leveraging the fact that railway vehicles operate on predefined trajectories. Track data is imported in GeoJSON format into Unreal Engine (UE), where it is used to construct a virtual track. A virtual locomotive model matching the real train in geometry, axles, and bogies is constrained to this track. Virtual sensors are then positioned to mirror the placement of their real counterparts on the locomotive. Together, the real track layout, realistic vehicle model, and accurate sensor placement ensure a faithful geometric representation.

In addition, sensor-specific measurement principles are modelled. A LiDAR module from Vir2Rail is adapted, and a camera module is newly developed. Both can be parametrized to replicate the behaviour of their real-world counterparts and tag which pixels/points belong to specific virtual objects.

Scaled Implementation

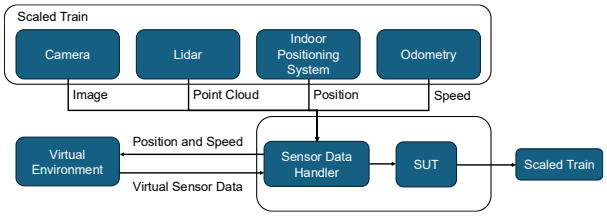


Figure 4 Concept: MR within the Scaled Environment

Figure 4 illustrates the implementation of MR within the scaled environment. The scaled train is equipped with an RGB camera, LiDAR, an odometry sensor and an indoor positioning system serving as a GNSS surrogate (Hofmeier and Cichon 2025a). A Jetson Nano is used for data processing and train control. For each test scenario, the selected track for the real train and its virtual replica is defined in advance, together with the identifiers and spatial coordinates of the augmented objects.

The functionality for augmenting virtual obstacles, introduced in Figure 3, is implemented in the sensor data handler. This component is coupled with the virtual environment in UE, which includes virtual sensor models aligned with the physical sensor setup of the SuT similar to (Hofmeier and Cichon 2025b). All sensors provide their information to the sensor data handler running on the Jetson Nano. The handler forwards the train position and speed to the virtual environment. Based on this information, the virtual train is aligned with the track in the virtual world. Once the virtual train is positioned, virtual sensor data is generated and sent back to the sensor data handler. The handler then combines the real and virtual sensor data and forwards the combined output to the SuT.

The SuT processes this enriched data stream without knowledge of the augmentation and controls the scaled train accordingly.

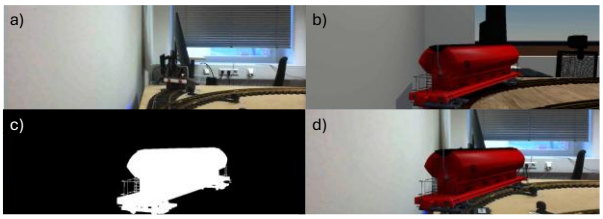


Figure 5 Results Scaled MR Camera

Figure 5 illustrates the augmentation process by combining a real image (a) with a virtual image (b) using a virtual segmentation mask (c), resulting in the final MR image (d). The augmented image is generated by fusing real and virtual images based on the mask. Pixels corresponding to white regions in the mask are taken from the virtual image, while pixels corresponding to black regions are retained from the real image. Consequently, the virtual wagon is seamlessly integrated into the real scene, producing an image that contains both real and virtual elements.

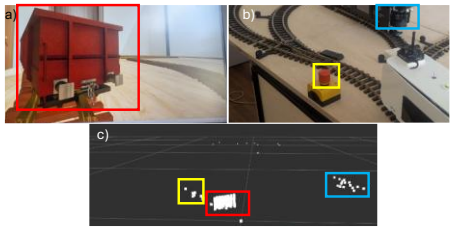


Figure 6 Idealized Results Scaled MR LiDAR

Figure 6 illustrates LiDAR augmentation in the scaled environment, showing the original scene (a), the virtual scene (b), and the resulting combined point cloud (c). The virtual wagon can be seen augmented into the real point cloud; for better visualization, all ground points were removed. The virtual point cloud is generated using ground truth point to object mapping and merged with the real data. To model realistic occlusions, a spherical occupancy grid based on LiDAR azimuth and elevation bins is created, allowing real points behind virtual objects to be removed (Manivasagam et al. 2023).

Transfer of the Method to Full Scale

After developing the methods within the scaled environment, the method was transferred to full scale. To enable scalability, recorded but unprocessed data is used. The data was recorded within the Munich Nord Cargo Yard using a class BR 294 locomotive with an in-house sensor setup. The locomotive and the associated track infrastructure were already available within the UE environment from previous work, which served as the basis for the development of Vir2Rail (Hofmeier 2026). Finally, virtual sensors had been placed at their real counterparts' positions while also adapting the sensing principles to follow their real counterparts.

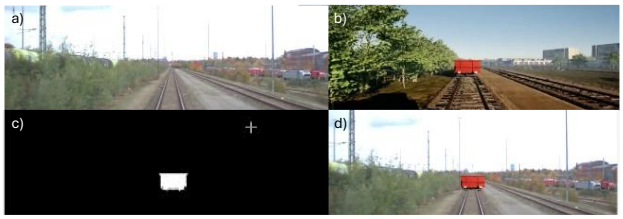


Figure 7 Results Full Size MR Camera

Figure 7 illustrates the fusion of virtual and real camera data on the shunting yard recordings augmenting a virtual wagon. The arrangement of the images within Figure 7 is similar to Figure 5.

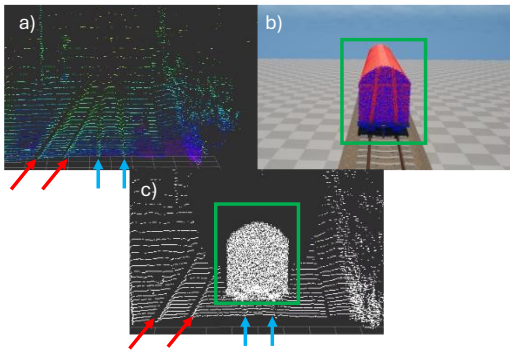


Figure 8 Results Full Size MR LiDAR

Figure 8 shows the full-scale MR Lidar scenario with a) the real scene, b) the virtual scene and c) the combined scene. The methodology is similar to the scaled approach. Both camera and LiDAR augmentations show that the concept in general is applicable.

Outlook

This paper demonstrates the feasibility of the proposed MR concept for enhancing railway field testing through the rapid generation of safety-critical scenarios. However, several challenges remain. First, the method requires more comprehensive validation by comparing the SuT response to virtual and real obstacles, as well as through pixel- and pointwise analyses of virtual and real scenes. Second, the visual quality of inserted objects, particularly for camera-based perception, is affected by inconsistent lighting. This will be addressed by AI-based lighting adaptation using environmental light sensors, which will also enable realistic shadow generation. Furthermore, the current approach depends on accurate track-related data to represent train movement within the virtual environment. Future work will investigate the use of rail detectors to automatically map objects to the railway infrastructure, reducing this dependency. Additionally, the framework will be extended by dynamic virtual objects that can react to real obstacles. Finally, the method shall also be applied in real time at full scale.

Acknowledgements

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