SN Computer Science (2025) 6:995
https://doi.org/10.1007/s42979-025-04529-6

ORIGINAL RESEARCH

Scaled Model Development and Testing for Automatic Train Operation: Creating a Digital Twin

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Received: 18 November 2024 / Accepted: 11 November 2025

Abstract

This paper explores the fundamental aspects of on-sight Automatic Train Operation (ATO) in environments without external protection. Development and testing face significant challenges due to the lack of available test vehicles and tracks, caused by high costs and logistical or operational constraints. A scaled model approach is proposed to address these challenges. The primary objective is to demonstrate how scaled models can overcome these barriers, focusing on object detection, localization and digital twins. The research employs a scaled model to address the key challenges associated with on-sight ATO in unprotected environments. The implementation of object detection was achieved through the utilisation of LiDAR sensors, enabling real-time obstacle identification similar to full-scale systems. Localization was achieved using ultrasonic sensors as a scaled GPS substitute, and a camera-based approach. A digital twin of the laboratory was created in Unreal Engine, using an in-house virtual railways environment to simulate vehicle sensors and compare with real-world data in further work. The scaled model demonstrated real-time object detection using LiDAR and precise localization with ultrasonic and camera-based methods. The digital twin accurately simulated the environment, enabling comparisons between simulated and real-world sensor data, providing insights that are difficult to obtain from real-world testing alone. The study confirms that scaled model development, offers a practical solution for advancing on-sight ATO. Moreover, the results suggest that further exploration of these capabilities within scaled models is essential for optimizing the product development process of ATO functions, potentially leading to more efficient and cost-effective innovations in the field.

Keywords Automatic train operation · Scaled model · Obstacle detection · Localization · Digital twins

Introduction

The climate policy framework for the upcoming decades demands a significant transition from road transport to more sustainable alternatives, with rail transport emerging as a key solution [1]. To make rail a competitive alternative to road transport, it is crucial to address the existing challenges faced by both passenger and freight rail services. Passenger rail systems often grapple with issues such as overcrowding, organizational inefficiencies, high costs, limited train availability, delays, and concerns related to boarding, luggage handling, and safety [2]. In the domain of rail freight transport, a clear distinction exists between full train services and single wagonload operations. While full train services efficiently handle large volumes of cargo with uniform origins and destinations, single wagonload transport, which must compete with road transport, faces challenges like reduced last-mile flexibility, poor predictability, and high operational costs, particularly due to the shunting processes [3].

These challenges highlight the need for optimization, where automation and digitalization can serve as transformative factors [4, 5]. Several successful automation projects have already been implemented, illustrating the potential for further advancements. The grade of automation (GoA) is defined within the GoA system. This, in turn, is determined by the tasks performed by the driver or automated system and ranges from GoA 0 on-sight operation to GoA 4 unattended operation [6].

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Published online: 03 December 2025

The first GoA4 system went into operation in Kobe, Japan in 1981 as part of a closed system [7]. Automation in European metros followed, with a major milestone in 2008 when the U2 and U3 lines in Nuremberg, Germany, opened, allowing mixed operation of automated and non-automated trains [8]. These systems are largely closed, minimizing external interfaces and facilitating automation through infrastructure monitoring at critical points. In Hamburg, the S-Bahn advanced rail vehicle automation with ATO over ETCS. Passenger services run under GoA2 (automated with driver supervision), while depot operations are fully automated (GoA4) [9]. In Australia, Rio Tinto's auto haul project employs fully automated rail vehicles with radio remote control. Safety measures such as the monitoring of level crossings and inhabited areas mitigate risks such as collisions with animals. The system detects impacts and allows remote decisions on whether to continue the journey [10].

These systems, which operate in safe, low-risk environments, highlight the need for new solutions to enable automated rail operations in more complex and high-risk scenarios. In general, the implementation of automation in railroad systems is divided into two principal categories: operations on mainline railways, where control systems such as train protection and interlocking technologies are used, and operations on secondary lines, where trains often use on-sight operation. To advance these areas further, it is essential to address their distinctive characteristics.

In main line operations, train control systems with signals are employed to regulate the movement of vehicles. This is due to the impracticality of direct monitoring to determine braking distances, given the considerable distances that must be traversed in the event of an emergency stop. Signals are employed to partition the tracks into discrete blocks, thereby regulating both occupancy and speed [11]. For automated mainline operation, the European Train Control System (ETCS) is already in use and offers different grade of automation within its levels from 0 to 2 [12]. Nevertheless, the extensive implementation of these systems will necessitate a significant investment in infrastructure [13].

On-sight operation requires the performance of more intricate operations, such as depot movements and shunting at reduced speeds. In such instances, the vehicle driver is responsible for monitoring stopping distances directly. In automated systems, the driver's sensory inputs are replaced by integrated sensors, including cameras, LiDAR, and radar. It is of high importance that accurate localization on the track plan be achieved [14].

The development of these complex systems requires a high level of development and testing to ensure the required level of railway safety. In general, the on-sight mode of operation is very similar to the problems encountered in the automotive sector. Studies carried out within the Pegasus project [15] have identified a scenario-based approach as a common practice for such scenarios.

Subsequently, a method adapted for railway technology is developed in [16]. This approach is based on a knowledge base that includes operational regulations, field observations and self-generated data. Similar to the automotive industry, this method emphasises simulation testing followed by thorough validation and verification in real-world environments. This approach is further developed in [17], which moves further away from the auto-motive approach and now includes a seventh layer of scenario design that considers additional rail-related issues such as the shunting order, which is mandatory for any movements on e.g. shunting yards and holds additional information for routing, and mission targets.

In [18] the use of virtual environments for the development of highly automated rail vehicles is demonstrated, suggesting that virtual pre-development is feasible. However, these simulations have not been sufficiently verified and validated, and there is no commercially available platform for on-sight ATO functions. Field tests using this methodology are still under development and lack sufficient validation.

Based on the research group's experience with automated on-sight rail systems, several challenges remain for simulation and field testing. In simulation, the rapid evolution of sensor technologies is a challenge, as adequate sensor models need to be developed first. The low demand for rail vehicle simulation environments has resulted in a limited number of commercial providers, making it difficult to keep pace with sensor advances. As a result, development often relies on unvalidated sensor models that, although based on prior knowledge, may not provide a fully reliable foundation [19].

Field testing has its own challenges. Rail test sites operate under strict regulations, requiring an operational and technical test manager in addition to test and development personnel. High rail infrastructure utilisation limits the availability of test tracks, and maintenance backlogs further complicate field operations. The cost of testing, including infrastructure use, shunting services and any locomotive upgrades, can reach several thousand euros per day [19].

To maximise the efficiency of field trials, simulation results must be highly transferable to the real environment. However, this is often hampered by non-validated simulation data and unforeseen hardware issues. Reducing the gap in technology maturity between simulation and reality is critical. The use of scaled models is proposed in [19] as a cost-effective solution to deal with this problem. This paper summarises the general state of the art in the development and testing of railway vehicle technologies in a scaled model and deals specifically with the results of the research group to date. In addition, a novel methodology is presented, based on the previous scaled model findings, for the development of digital twins for the validation of virtual environments (especially their sensor simulation) and their preparation for the formation of digital twins for real-time verification of virtual environments in the field application.

Approaches in Railway Research and Engineering

The advancement of ATO necessitates the establishment of trustworthy methodologies for development and validation that balance realism, cost efficiency, and scalability. Two methodological pillars have emerged in railway research to address these challenges: scaled physical models and digital twins.

Scaled models facilitate the cost-effective replication of complex railway environments and enable iterative hardware and software testing under realistic yet controlled conditions. Digital twins, in contrast, provide a dynamic link between physical assets and their virtual representations, offering powerful tools for simulation, monitoring, and predictive analysis. The combination of these approaches constitutes a complementary foundation for the advancement of automation in railway systems, forming the basis for the methodology that will be presented in the following sections.

Scaled Models in Railways

Scaled models are widely utilized in railway vehicle research and education. For instance [20], demonstrates the use of a scaled model with a 5-inch track gauge to validate dynamic simulations. At TU Dresden, an H0 gauge (16.5 mm) model system is used for teaching and research, focusing on safety and interlocking technology, with capabilities to connect to real systems like the Dresden S-Bahn [21]. Similarly, RWTH Aachen operates an H0 gauge environment featuring realistic interlocking technologies, real interlocking simulations, various safety systems including ETCS, and a comprehensive route network for optimizing driving services [22].

These examples have demonstrated the usefulness of using scaled models for railway applications, which was the starting point for the research group's activities on the use of scaled models for ATO. In the state of the art there are research approaches focusing on the realization of a scaled ATO system to improve test and development methods for hardware and software dedicated to ATO functions [19].

Furthermore [23] deals with the improvement of localization methods in order to provide a basis for further optimization of the functions in the field and to develop the precision and sampling rate of localization for direct use of the results in the scaled model. The methods and results developed in this research are presented below, for further clarification of their usage and importance in the digital twin development.

To investigate ATO functions within a scaled model, it is crucial to establish a test field and demonstrator vehicle tailored to the specific requirements of automated shunting operations. The test field replicates a marshalling yard environment, incorporating elements such as arrival tracks, a hump, and directional tracks. Key shunting use cases [24], such as "move," "approach," "attach," and "check" are performed within this setup to evaluate the functionality of the ATO system.

The demonstrator vehicles, central to these investigations, are equipped with a range of sensors and computing devices necessary for automated driving. The core processing unit is a Raspberry Pi 4B 8GB, interfaced with various sensors, including ultrasonic beacons, LiDAR, and cameras, to facilitate environment detection and localization. These components are housed within a G gauge model (scale 1:32), which provides sufficient space to accommodate the necessary hardware while keeping infrastructure costs manageable [19].

The ATO system on the demonstrator vehicle is designed to process high-precision localization data, crucial for distinguishing between obstacles and ensuring safe operations. The system integrates sensor data from various sources to make driving decisions, with the localization primarily managed by the Marvelmind Indoor Positioning System (IPS), which uses ultrasonic signals for precise positioning. The IPS is supplemented by additional sensors such as LiDAR and cameras, which are used for environmental detection and provide redundancy in the event of localization problems in further projects, such as by SLAM methods [19, 23].

The test environment is designed to simulate a variety of operational scenarios relevant to ATO systems, especially those encountered during shunting operations. The approximately 34 m of track in the test environment, along with 17 switches and two three-way switches, create a versatile setup for testing. This number of switches is comparable to the entry group of a freight marshalling yard. In practical applications, three-way switches are not as widely utilized due to their increased system complexity. In [25], the realism of scaled model environments for ATO is examined in greater detail, highlighting both limitations and potential applications. Based on this configuration, it is possible to implement a range of shunting activities, such as "move," where the locomotive switches tracks via a dead-end track, and "approach," where the locomotive safely approaches an obstacle or another wagon [19].

The use of the Marvelmind Indoor Positioning System (IPS) in the scaled environment is particularly noteworthy. This system employs ultrasonic beacons to determine the position of the demonstrator vehicles with high accuracy. The beacons, strategically placed around the test environment, communicate with mobile units attached to the vehicles. The system operates by measuring the time-of-flight of ultrasonic signals, which is then used to calculate the position of the vehicle in the test environment. This method, while effective, has certain limitations, particularly in areas where ultrasonic signals may be reflected or obstructed, leading to potential inaccuracies in positioning [23].

To mitigate these challenges, the system is augmented with additional sensors like odometry and routing data. The integration of odometry data using a Kalman filter enhances the accuracy of the localization process. By combining the data from the various sensors, the system can compensate for potential errors in the ultrasonic positioning, such as signal reflections or obstructions. The Kalman filter helps to smooth out these errors by estimating the vehicle's position based on both current sensor readings and previous data points, resulting in a more accurate and reliable positioning system. In addition, the orthogonal projection of measured points on the routing data eliminates the lateral deviation, leading to a more reliable and precise localization [23].

Furthermore, a camera-based localization method has been developed to address the limitations of the IPS. This approach involves using high-resolution (4 K) cameras mounted on the roof of the test environment to monitor the position and movement of the demonstrator vehicles. The cameras are capable of capturing wide-angle images, which are then processed to extract features that can be used to determine the vehicle's position [23].

The camera-based system operates by capturing images at a high frame rate and processing these images using feature-based algorithms such as SURF (Speeded-Up Robust Features). These algorithms identify key features within the images, such as edges or corners, which can then be matched across successive frames to track the movement of the vehicle. This method provides a high level of accuracy, particularly in dynamic environments where the vehicle is in motion [23].

To ensure the accuracy of the camera-based system, the images captured by the cameras are processed using advanced image stitching techniques. This involves combining images from multiple cameras to create a single, cohesive view of the environment. Feature-based algorithms are particularly effective for this purpose, as they are able to identify and match features across different images, even in the presence of distortions or varying perspectives. The SURF algorithm, in particular, has been shown to provide a high number of reliable features relative to processing time, making it well-suited for this application [23].

The fused image data is then used to calculate the position of the vehicle within the test environment. This process involves transforming the pixel coordinates of the detected features into world coordinates, which are then compared with the data from the ultrasonic system. By integrating the data from both systems, the overall accuracy of the localization process can be significantly improved, allowing for more precise control of the vehicle during shunting operations [23].

The camera-based localization system has demonstrated superior accuracy compared to the ultrasonic system, particularly in dynamic scenarios where the vehicle is in motion. Its ability to capture and process high-resolution images allows it to maintain precise positioning even as the vehicle navigates through a complex track layout. However, the current hardware configuration limits the system's real-time processing capability, leading to delays in positioning updates. This limitation will be addressed in further development. Despite these challenges, the camera-based system offers significant advantages, especially in environments where signal reflections or obstructions could hinder the accuracy of ultrasonic positioning. With future hardware upgrades, the system's potential for providing high-resolution, real-time data on the vehicle's position and surroundings makes it a valuable tool for the development of ATO systems in complex or dynamic environments [23].

The experiments on the scaled model underscore the camera-based localization system's improved accuracy and reliability over the ultrasonic system. However, further optimization is necessary to enhance its real-time capability, ensuring its viability for real-world applications. Despite its current limitations, the camera-based system shows great promise for integration with ATO systems, offering a robust solution for precise localization in automated railway operations [23].

These findings highlight the importance of using advanced localization methods, such as camera-based systems as back-up or redundancy option, in developing highly automated ATO functions. The successful implementation of these technologies in a scaled model environment sets the stage for further advancements in the field, including the integration of these systems into full-scale railway operations. The ongoing development of a digital twin in Unreal Engine 5 (UE5) will further bridge the gap between the physical and digital realms, enhancing the overall capability and robustness of the ATO systems under investigation.

This comprehensive approach to developing and testing ATO functions within a scaled environment not only provides valuable insights into the performance of different localization methods but also lays the groundwork for future advancements in railway automation. The presented methods illustrate the substitution of typical ATO sensors by scaled or representative technologies. For localization, it has already been shown that the system behavior and deviations follow realistic patterns when considering geometric scaling factors. Further research will investigate whether similar relationships can be established for additional sensors, or whether data from the scaled system needs to be artificially adapted, for example by adding noise. In this way, the applicability of the sensor setup to full-scale systems can be assessed and justified. By leveraging the strengths of both ultrasonic and camera-based systems, this research aims to create a more robust and reliable ATO system that can be effectively scaled up for use in real-world applications. The integration of these systems with a digital twin further enhances the potential for real-time monitoring, control, and optimization of automated railway operations. The primary advantage of the initial phase is the creation of a digital twin within the scaled model, which serves to verify and validate corresponding simulation models or environments. The implementation of scalable interfaces between the digital replication, scaled model, and real-world application ensures the efficient transfer of technology to the field when the technology within the scaled model has reached a sufficient level of maturity.

Digital Twins in Railways

The concept of a digital twin has emerged as a transformative tool in a number of different industries, offering a dynamic virtual representation of a physical system. In essence, a digital twin entails the generation of a comprehensive, real-time digital replica of a tangible asset, system, or process. This replica is continuously updated with data from the physical counterpart, thereby facilitating real-time monitoring, simulation, and analysis. The digital twin functions as a conduit between the physical and digital realms, facilitating a more profound comprehension of system behavior, predictive analysis, and optimal decision-making [26].

In recent years, digital twins have gained significant traction across a number of industries, particularly in manufacturing, aerospace, and healthcare, where they are used for predictive maintenance, performance optimization, and anomaly detection. By simulating potential scenarios and predicting outcomes, digital twins permit organizations to address issues in advance of their manifestation in the physical world, thereby reducing downtime and improving efficiency. The railway industry has also commenced the adoption of digital twin technology, recognizing its potential to enhance operational efficiency, safety and maintenance practices. In the context of railways, digital twins are being employed with increasing frequency for predictive maintenance purposes. This involves the analysis of real-time data from trains and infrastructure components in order to predict potential failures and schedule maintenance before issues arise. This approach not only extends the lifespan of assets but also minimizes disruptions to service, thereby enhancing the overall reliability of rail networks [27].

Furthermore, digital twins are being investigated for their potential to enhance railway operations, including the management of traffic flow and the improvement of energy efficiency. By creating a virtual representation of the entire rail network, operators are able to simulate a variety of scenarios, including changes in traffic patterns or the impact of infrastructure upgrades. This allows them to identify the most efficient and effective strategies for managing the network [27].

In addition to the applications of predictive maintenance and network optimization, digital twins are also being utilized in more specialized contexts within the railway sector. A digital twin-based approach for automatic train regulation has been proposed, addressing the challenge of integrating dispatching and real-time control and thereby improving punctuality and operational robustness in complex traffic scenarios [28]. A cloud-based framework for railway vehicle dynamics simulation has been introduced to address the challenges of scalability and computational efficiency by leveraging cloud resources to outsource complex simulations, thereby facilitating flexible and rapid evaluation of vehicle behavior under varied conditions [29]. Additionally, a simulation-based digital twin for railway stations has been developed to address the critical challenge of predicting and managing passenger flows during both normal and emergency situations, providing support for proactive decision-making and risk mitigation [30]. These studies underscore the expanding versatility of digital twin technologies across various railway domains. Concurrently, they illustrate how current research is driven by the need to overcome integration, scalability, and safety challenges.

Digital Twin Development Via Scaled Models

In the specific context of ATO systems, digital twins offer a unique opportunity to advance the development and testing of highly automated rail vehicles. The capacity to construct an exact digital replica of the physical environment and the vehicles that operate within it permits comprehensive testing and validation of ATO functions in a regulated, virtual setting. This approach is particularly valuable for on-sight ATO, where the complexities of real-world environments cannot be adequately replicated or tested in physical trials alone.

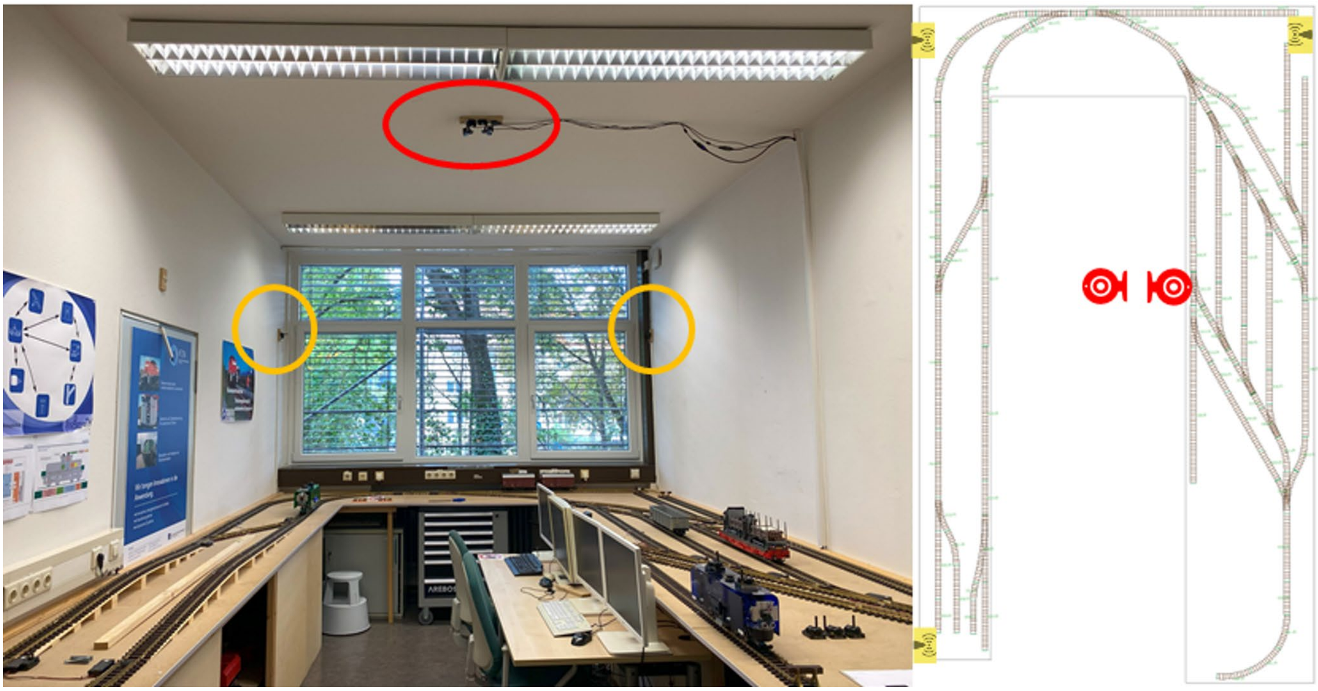

Fig. 1 Overview scaled test environment, cameras (red), ultrasonic beacons (yellow) [23]

Fig. 2 Scaled demonstrator with (a) Raspberry Pi, (b) Arduino Nano, (c) Marvelmind Beacon, (d) Rotary Encoder, (e) Strain gauge, (f) RGB camera, (g) Ultrasonic sensor, (h) LiDAR [19]

The comparison of real-time data from the physical model with the digital twin also allows for the verification of the virtual models, thereby facilitating improvements reducing the time-consuming data acquisition in the field.

The following sections will examine the methodology for the creation of a digital twin for on-sight ATO development, based on an inhouse ATO simulator. The process will commence with the construction of a scaled test setup and will subsequently address the interconnection between the physical, scaled, and digital models.

Scaled Model Test Area

The test field is built on a U-shaped plate, as shown in Fig. 1 (left). The track plan is shown in Fig. 1 (right). The positions of the ultrasonic beacons (yellow) and the cameras are also labelled.

The ultrasonic beacons cover as large a triangle as possible to ensure optimum coverage. The cameras are positioned in the center of the ceiling and provide sufficient FoV to completely cover the test field. Further information on the design of the test field can be found in [19] and [23].

The test vehicles are constructed as shown in Fig. 2 and have a specially designed body based on G-gauge bogies in order to carry the large number of sensors and processors for the further development of ATO functions.

Specifically, the vehicles have the following equipment: The central unit is a *Raspberry Pi 4B 8GB* (a). Two *Arduino Nano* (b) are used to read out sensor data. The localization is implemented with an ultrasound-based *Marvelmind Indoor Positioning System* with mobile hedges on the vehicle (c) and fixed beacons at the labs walls. To record odometry data, an incremental encoder (d) is attached to the engine shaft. A strain gauge is installed in (e), which can be used to measure the trailer load. An RGB camera *RPI WWCAM* (f), an ultrasonic sensor *HC-SR04* (g) and a LiDAR sensor *RPLIDAR M2A8* (h) are used as sensors for environment detection [19].

Due to its 1-layer point cloud, the LiDAR is relatively under performing in LiDAR-based object classification and has since been replaced by a Unitree 4D-LiDAR L1 PM for further research in this area.

The system is equipped with UDP interfaces to exchange the position, speed and other data not relevant to this work with the central laboratory computer. This data is to be used to mirror the physical laboratory in the digital environment.

Unreal Engine Based ATO Simulation

In order to create a real-time digital twin for ATO systems, it is essential to establish a simulation environment that accurately reflects the characteristics of the vehicles and the environments in question. The research group has been engaged in the development of such systems for a number of years. The fundamental functionalities necessary for the construction of the digital twin are elucidated below. Further information about the simulation environment and the research done within it can be found in [16, 18] and [31].

In the initial stages of developing a simulation environment, there are a number of potential avenues for exploration. Given the conceptual synergies that exist, it is possible to utilize virtual environments from the automotive sector as a basis for the 'driving on sight' concept. However, preliminary tests have demonstrated that these systems were unable to be designed with sufficient flexibility to respond adequately to railway-specific features, because they are closed systems from suppliers already available on the market, limiting their adaptability for customization. The available simulation environments typically only include a limited set of virtual elements, such as highways, cities, or suburbs, and lack essential railway-specific assets like trains or railway signals. As a result, these environments do not provide a cost- or time-efficient way to extend them for railway research applications. Nevertheless, sensor systems with similar or identical functionality, such as LiDAR, can offer synergies that can be exploited in a specially developed environment.

In light of the availability of suitable virtual environments on the market, the decision was taken to develop a bespoke simulation environment for highly automated rail vehicles (with a particular focus at on-sight operation), one that would afford the requisite flexibility for scenario-based testing and development. At the outset of the development process in early 2022, a number of simulation frameworks were available for consideration, including Unreal Engine 4, Unreal Engine 5 and Unity. In the preliminary analysis, UE5 was identified as the optimal choice due to its superior performance in terms of virtual sensors, high-resolution environments, and a comprehensive range of add-on modules.

The initial stage of the process is to create a realistic environment that accurately reflects the sensor data. This is achieved through the utilization of the UE5's intrinsic landscape functionality. This enables the mapping of actual topographical features within the engine by importing elevation maps in PNG format. The most time-consuming aspect of this process is the acquisition of high-resolution elevation maps. It is recommended that the maps be provided on a 1 m x 1 m grid in order to ensure the most accurate representation possible. Such high-quality elevation maps are available, for instance, in the BayernAtlas [32].

Subsequently, the infrastructure components are installed, commencing with the tracks. The UE5 pro software provides an appropriate framework (for further information see the UE5 documentation [33]) for this purpose, offering a spline function that is well-suited to the task. An integrated mesh, for example a rail element, is drawn along a defined path and represents a complete rail. The UE5 *spline format* is compatible with the following data types: *X position*, *Y position*, *Z position*, *X-in tangent*, *Y-in tangent*, *Z-in tangent*, *X-out tangent*, *Y-out tangent* and *Z-out tangent*. This format is not analogous to conventional route information derived from map data, such as UTM coordinates or longitude and latitude. Nevertheless, contemporary tools or tutorials for mainstream programming languages (Python, Matlab, C++) are available for the conversion of traditional map data into the UE5 spline structure. It is thus imperative to obtain highly accurate route data in order to lay the tracks. This data can be obtained from BRouter [34] or OpenRailwayMap [35].

However, the elevation data is typically less precise than that found in pure elevation maps, and thus is not utilized further.

In contrast, the track splines are positioned within the virtual environment according to the X and Y coordinates above the landscape, with the elevation map serving as the reference point. The *ray-tracing/casting* function is employed to project a ray vertically down onto the landscape. This results in the generation of a hit event that encompasses the position and, consequently, the precise Z value of the spline point within the track. Subsequently, the track spline is projected onto the landscape for all points it contains, thereby creating a homogeneous course between the landscape and the track. This process also yields a higher accuracy of elevation values compared to the data provided by BRouter or OpenRailwayMaps.

In addition, other infrastructure components, such as catenary poles, the catenary itself, or lighting masts, can be generated automatically with the aid of the track spline, utilizing a predefined offset in the transverse direction at freely definable distances along the spline. The local coordinate system of the spline provides a straightforward solution based on the line length X from the start of the track, allowing objects to be placed at the desired position. An alternative approach is the placement of elements such as signals, buildings or masts based on map data from OpenRailwayMap. In order to achieve this, the conventional coordinates derived from the map data are transformed back into the UE5 world coordinate system (in cm), and the objects are then placed using the world coordinates. This procedure is equally effective as the aforementioned approach, though it may necessitate greater manual input for rectification in the event of discrepancies between the track and object coordinate databases.

Subsequently, it is essential to direct the ego vehicle, which is operated with the system under examination, through the environment. The UE5 simulation framework offers a number of possibilities for this. In general, the UE5 has a physics engine that is capable of calculating a range of physical effects, including forces, friction, damping, shocks and more, depending on the level of accuracy of the selected meshes. The contact between wheels and rails represents a highly complex scenario that necessitates the utilization of a mesh resolution at the finite element (FEM) level to ensure the generation of reliable outcomes. This results in a considerable burden on the physics engine, preventing the creation of a real-time simulation environment. Moreover, it is essential to configure the collision option to *"complex as simple"* for all objects that are to be identified by environmental sensing systems, such as the LiDAR simulation. It is only through the usage of this option that the 'real' collision of the object is employed, as opposed to a more simplistic box or polygon model. The *"complex as simple"* collision option automatically disables the option to utilize physics, thus avoiding an overload of the FEM-like calculations.

The possibility of moving objects using splines is employed to implement the vehicle movement. The splines are already available as a consequence of the track generation process. In the UE5 syntax, an object is moved via a spline based on an alpha value between 0 (the beginning of the track or spline) and 1 (the end of the track or spline). By using the *getSpline* length function, the alpha value can be modified via a continuously advancing *timeline component*, thereby enabling the vehicle to move at the desired speed.

In order to guarantee the correct behavior of the vehicle in the longitudinal direction, an external kinematics model has been constructed in MATLAB/Simulink. This model is capable of deriving realistic vehicle behavior from the target speed specified by the ATO system and feeding this back to UE5 as the actual speed via a UDP interface. The kinematics model receives the curve radius from the UE5 simulation, which is calculated from the torsional angle of the bogies. Additionally, other variables, such as vehicle masses, dead times, and other vehicle-specific properties, are stored directly in the vehicle model.

In principle, the spline-based motion can be coupled with an extended longitudinal dynamics model, which allows for the integration of parameters such as damping, friction, and external forces. Such a model can also account for higher-order effects, including sinusoidal running, pitch, roll, and yaw, which can be superimposed on the idealized spline trajectory. However, as clarified in [19], the G-gauge scale used in the physical setup is not suitable for investigating detailed wheel–rail mechanics. For such analyses, larger scaled vehicle models are more appropriate, as described in the literature. The present approach therefore focuses on ensuring realistic longitudinal behavior, while mechanical effects beyond this scope are left for future developments. For the transfer of the methodology from the scaled twin to digital twins of full-scale railway applications, the required level of simulation fidelity has to be re-evaluated, ensuring that the depth of modeling is appropriate to represent the relevant physical effects.

In the case of bogie locomotives, the vehicle is moved over the spline by means of the bogies, thereby creating a realistic lateral movement of the vehicle. The initial bogie is positioned over the spline, with the subsequent bogie following at the distance corresponding to the bogie pivot. The locomotive body and all attached elements, including sensors, are moved in relation to one another based on the center point and the rotation of the bogies (see Fig. 3). This results in a realistic pivoting movement of the center of the vehicle in tight bends, which constitutes the initial element of the transverse network (see image). Furthermore, it is possible to simulate effects such as sinusoidal motion in the kinematics model and apply them to the bogies or the digital image of the locomotive as additional lateral motion by extending the network interface. The same principle applies to pitch, roll, and yaw movements.

It is now necessary to conclude the simulation loop and provide the simulated data to the system under test or development. In the present simulation state, the data pertaining to localization, odometry, the camera and LiDAR are transferred from the virtual environment to the ATO system.

The simulated location data can be linked via the position of the origin in the world coordinate system of the virtual environment, via the position of the characteristic point shown at the origin (e.g. shunting yard dead-end, or switching points, etc.), as viewed in Fig. 4. Consequently, the simulated coordinates (in cm) are transformed by elementary mathematical operations into UTM or longitudinal and latitudinal coordinates, which are then processed by the ATO system.

The odometry data is already available in a simulated format from the kinematic model. Such data are either fed back to the ATO system unaltered or subjected to the addition of Gaussian noise, which serves to emulate the characteristics of the actual sensor.

The UE5, which originated as a game and film framework, incorporates a native camera simulation. A variety of parameters can be employed in the modelling of the camera types to be simulated. Furthermore, a variety of post-processing options are available for the visualization of lens

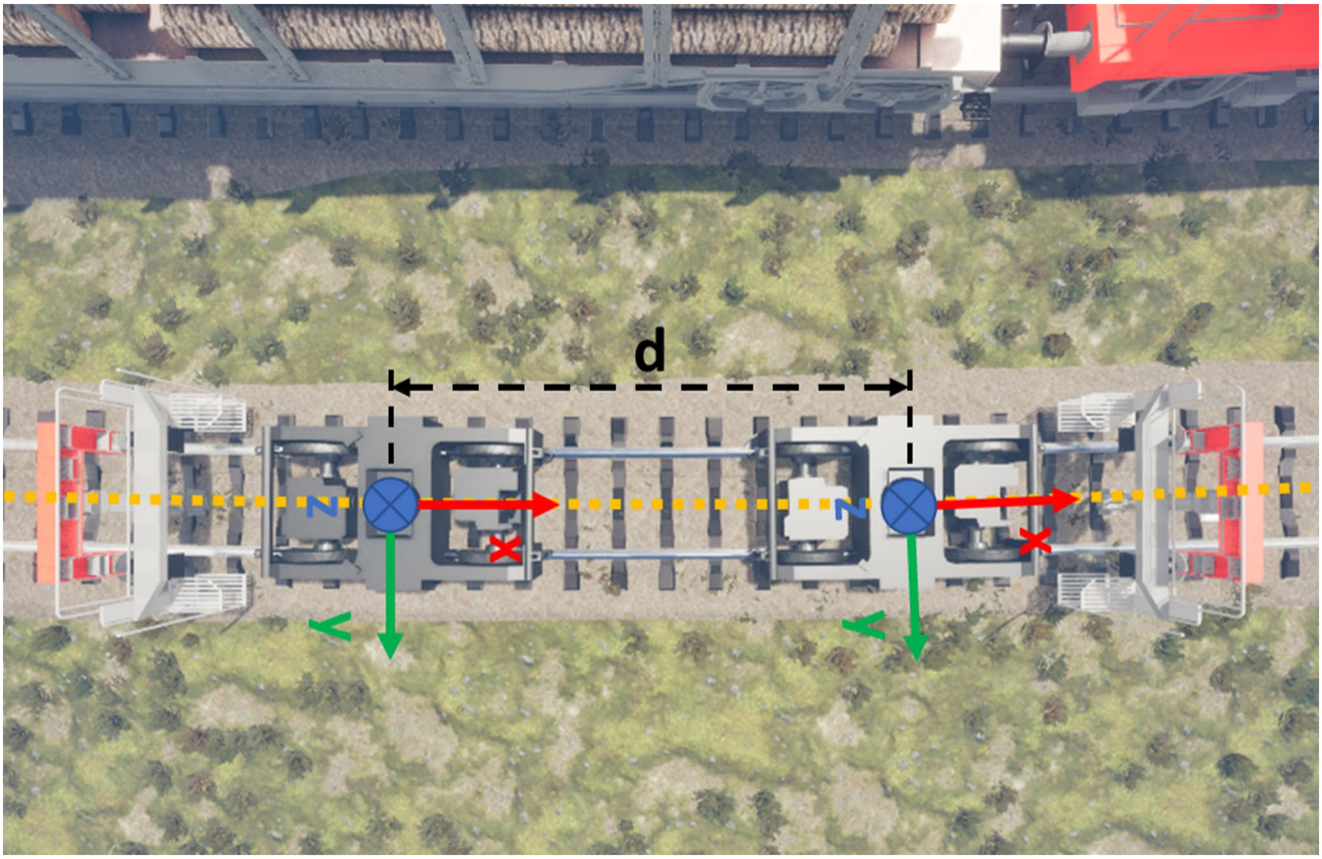

Fig. 3 Positioned Bogies on the tracks, bogie spacing (d) and spline data (orange)

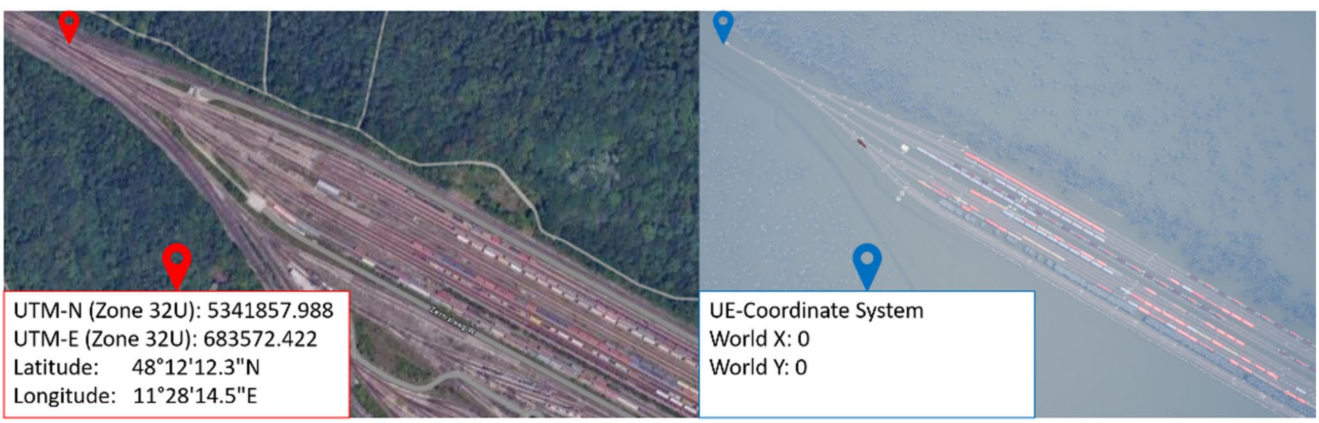

Fig. 4 Offset of real-world location (left, googlemaps) and simulated location (right, inhouse simulation environment) demonstrated at the shunting yard Munich North

effects and other distortions. To utilize the data, the camera module is linked to a network interface in order to process the image data within the ATO system.

The emulation of LiDAR data presents a more complex issue. The most crucial step in establishing a framework for point cloud emulation is to guarantee that the assets to be identified utilize their 'true cloud box' for collision calculations. In the context of LiDAR sensor simulation, there exists a multitude of well-established, state-of-the-art methodologies, each of which is tailored to address specific aspects of the intrinsic characteristics of LiDAR data [36, 37]. In general, ray tracing or ray casting is employed to generate a beam of rays that correspond to the scan pattern of the LiDAR sensor. This beam of rays then traverses the simulated environment, which is coupled to the origin of the virtual LiDAR. At each discrete time step of the sensor, the rays are evaluated for potential collisions with other objects. From a mathematical perspective, a straight line intersects a triangle that spans the mesh of the object that has been struck. The UE function *Hit-Event* provides the capability to calculate the world coordinates of the impact. The hit points are transformed into the local coordinate system by the translation and rotation of the LiDAR coordinate system, thereby forming an idealized point cloud that would be expected from a sensor with the set parameters (FoV, scan pattern and range).

These idealized point clouds provide a foundation upon which preliminary verification of the system response of the ATO system can be conducted. By disregarding material (re-reflection), sensor (detection thresholds, wavelength) and external (weather) characteristics, which manifest themselves as noise or a complete absence of points, a point cloud is produced that can be more reliably detected by object recognition algorithms.

In order to generate a more realistic virtual point cloud, it is necessary to take the aforementioned effects into account. For each of these effects, there are established state-of-the-art methods that are employed in the virtual sensor model utilized by the Institute in its own simulations. In order to account for material-induced noise, the detection probability of a reflected point is determined in accordance with [36] and [37]. Furthermore, the influence of weather effects, such as rain, fog or snow, is converted in line with [38].

The simulation environment thus provides the basis for the subsequent development of a digital twin for real-time ATO applications.

Connecting Physical and Digital ATO Systems Via Localization Data

The initial stage of the process is to define the physical assets that are to be incorporated into the digital twin and to transform them into a format that can be read by UE5. In the aforementioned example, this is the scaled test field, as previously described. It is essential that the digital twin is oriented within the boundaries of the room. The mapping of elements detected by the sensor should be carried out with an appropriate level of accuracy, while cosmetic accuracy is sufficient for room elements that have no direct impact on the ATO functions.

The core elements of the infrastructure environment are the walls of the test site, the floor slab of the track infrastructure and the workstation including monitors (see Fig. 5). Mobile assets such as locomotives and wagons must also be represented.

Fig. 5 Digital twin of the scaled test environment (compare to Fig. 1)

A variety of interfaces are available for integrating assets into the engine, as provided by UE5. Some elements, including flora, fauna, assorted materials, and vehicles, can be imported directly via the *UE5 Marketplace* or the *Quixel Bridge* plugin. The level of detail of the available assets varies considerably and is frequently unsuitable for a reliable virtual simulation environment for highly automated rail vehicles. It is necessary to add unavailable elements to the engine via additional interfaces.

The UE5 platform offers a variety of import formats, which are typically different types of mesh data, such as *.obj (wavefront) or *.fbx. Wavefront can frequently be exported from traditional CAD tools, including Creo, Inventor, Catia, and others. However, errors may occur when importing assemblies directly via *.obj. This issue can be addressed by a subsequent conversion to *.fbx, which can be performed in Blender, for instance.

Once the integration paths of the various elements have been established, the requisite assets are made available within the project in order to map the scaled test field in the subsequent step.

As with the construction of a virtual simulation environment for real railway vehicles, the initial step is the creation of the landscape, or in this case, the floor slab. The aforementioned elements are enclosed by the walls, ceiling, and floor of the test field. Furthermore, the desk and screen are positioned manually within the designated level. The subsequent phase of the process is the laying of the tracks. As previously indicated, it is necessary to provide an external database for the track plan. In this instance, the coordinates of the track were previously extracted from a high-precision three-dimensional scan of the room. The data is already available in the correct X, Y, Z format, and the incoming and outgoing tangents required for the UE5 spline structure can be calculated in the same way using tools that are currently considered to be state-of-the-art. The subsequent track laying process can be directly transferred from Chap. 3.1. The resulting UE5 Level is visualized in Fig. 5, already including the two scaled demonstrator locomotives.

Once the basic structure is in place, further refinement of the virtual environment can be achieved by adding detailed textures and lighting effects, ensuring that the simulation closely mirrors the physical test site. However, the precision needed in building an accurate environment depends strongly on the sensors that are used. For example, if only LiDAR data is of interest, there is no need to provide a clean visual look of the materials. The resolution of the asset meshes only needs to be as good as what the sensors' scan patterns and noise can detect in various positions during the test runs. Conversely, if camera data is also used, the mesh precision must be increased due to the (usually) higher resolution of the cameras. Additionally, there is a much higher requirement for the quality of the optical properties of the materials, such as reflectivity, roughness, material "colors," and similar attributes. This step is crucial for enhancing the visual fidelity of the digital twin, particularly in scenarios where interactions between the environment and the automated rail vehicles are being simulated. Additionally, thorough testing is conducted to validate the accuracy and performance of the digital twin, ensuring it meets the required standards for reliable simulation.

The locomotives are already designed in a CAD-Tool to 3D print, laser cut and bend the different custom parts. This means the loco is transferred into the UE5 project via the mentioned import paths, separated in the two bogies and the loco's main body featuring all the additional elements as sensors, processing units and so on, visualized in Fig. 6.

Once the required assets have been integrated into the UE5 project, the next step is to establish functionality that enables interaction between the physical and digital laboratories. The position data used for synchronization is already available via a UDP socket on the simulation PC. Additionally, the UE5 project is equipped with multiple UDP interfaces for communication with other modules. To process the position data, an existing interface, originally designed to read simulated real-time speed, will be repurposed. This interface is no longer needed in the "Digital Twin" operational mode of the simulation environment. The position data of the demonstrator vehicles, derived from the ultrasonic system, is thus available within UE5 at a sampling rate of approximately 80 Hz.

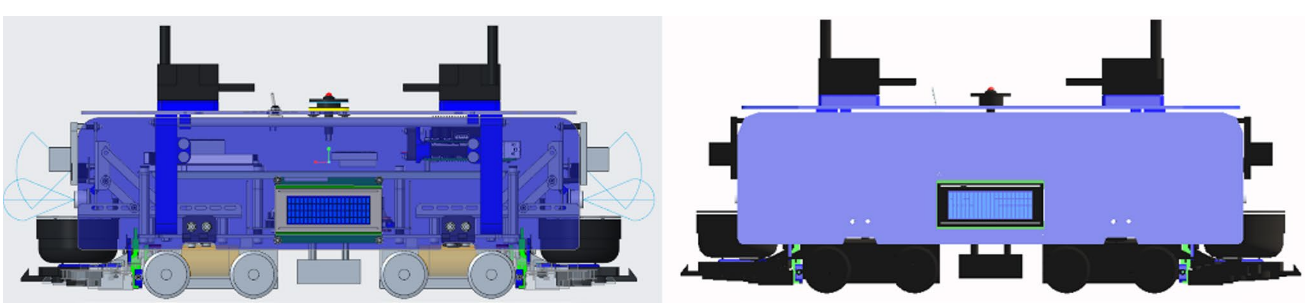

Fig. 6 CAD-data (left, creo parametric) and unreal asset (right, unreal engine)

The next step involves adapting the vehicle maneuver execution to these new data inputs. There are several possible approaches for implementation. One approach could involve directly placing the vehicle within the level based on the captured positions of the two beacons. However, this would require modifications to the existing spline-based movement system, making it difficult to switch between the traditional simulation and the digital twin modes. Moreover, this method would directly incorporate any potential measurement errors from the beacons into the object placement, which could significantly compromise the digital twin's validity in comparing real and simulated sensor data.

Instead, the vehicle's movement will continue to follow the predefined spline, ensuring the vehicle remains track-bound and maintaining the precision required for accurate alignment between the physical and digital environments. In this process, only the position of the front bogie (in the direction of travel) is read, and the simulation is provided with information on which route has been set in the real laboratory, delivered in spline format, corresponding to the demonstrator's route during the test.

The measured position, received via UDP, is then used in conjunction with the spline component and the *Find Location Closest to World Location* function to perform an orthogonal projection to identify the nearest point on the spline relative to the measured position. In the next step, this information is converted into a "distance along spline" value, which is then used to calculate the alpha value. This alpha value is subsequently employed with the Timeline component to correctly position the vehicle within the simulation environment. For this purpose, the spline component and the previously determined point on the spline are used in the *Get Distance Along Spline at Spline Point* function. The process is illustrated graphically in Fig. 7.

With this, the connection between the physical laboratory and the digital representation is successfully established, enabling the commencement of initial verification approaches, which will be discussed in more detail in the next chapter.

Results

Before discussing the results of the described test setup, it is important to first recap the original goals and reasons behind the approach. The development and testing of increasingly complex on-sight ATO systems require extensive testing, which, due to the sheer volume and variety, is ideally conducted through simulation. The development of simulation environments has now also reached the railway

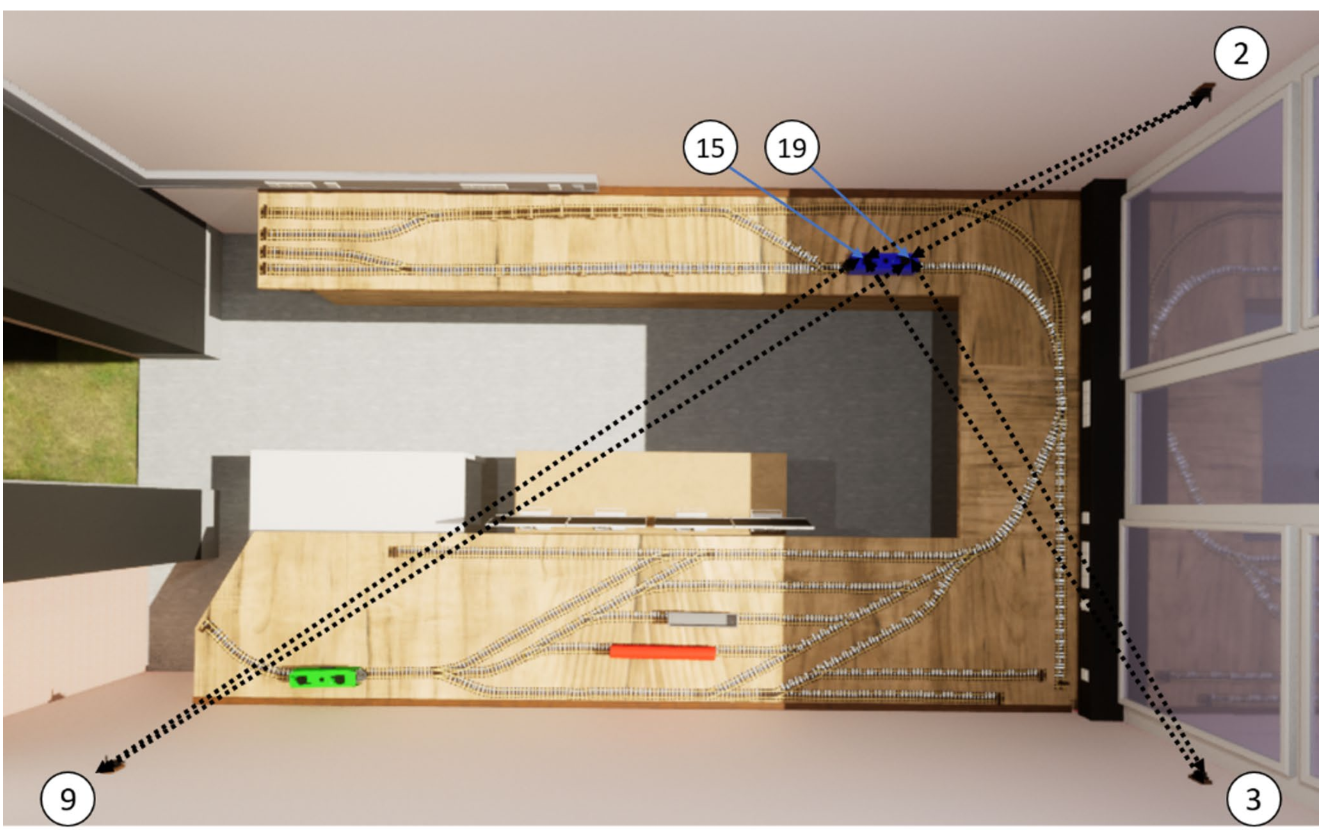

Fig. 7 Measurement of the distances between the beacons within the digital twin

Table 1 Deviations of ultrasonic- and camera-based localization [23]

Test Case	Ultrasonic	Camera
Static	± 3 mm	-
Dynamic	± 60 mm	± 37 mm
Consistency	± 15 mm	± 12 mm

sector, although with some delay compared to the automotive sector. The development of such environments always requires a sufficient data base of real-world measurements to ensure reliable models. However, acquiring this data in the railway industry is challenging due to complex organizational processes, scarce availability of test infrastructure, and vehicles. The previous developments around ATO functions in the scaled model have proven that it can serve as a simple and cost-effective alternative to real test sites. The validation of simulation environments within a digital twin creates unique opportunities through the synchronous linking of real and virtual datasets. Consequently, the preceding discussion outlined how such a digital twin can be constructed to provide a foundation for further analysis of the simulation modules.

The initial evaluation assesses the precision with which the position of the ultrasonic system is conveyed to the digital twin. The ultrasonic measurement system provides the unprocessed distances between the beacons. These constitute the basis for the evaluation. In order to obtain these distances from the digital twin, the ultrasonic beacons, which were previously only displayed as a mesh, are converted to reflect their actual function. In order to achieve this, the beacons affixed to the wall are designated as fixed beacons, while those mounted on the demonstrators are classified as hedges. The hedges are programmed to calculate distances on a continuous basis, utilizing the *get world location* function for the respective components and the 'get distance between (input world location beacon, world location hedge)' function. It is essential to ensure that the origin of the simulated beacons is aligned with the source of the loudspeaker/receiver, in order to achieve conceptual results that are consistent with those observed in the physical twin. Table 1 lists the deviations determined in [23].

The static deviations are associated with the mean value of the measurements at standstill, whereas the dynamic data obtained during travel is related to the track coordinates. As previously described, these coordinates originate from a high-precision 3D scan. The consistency data indicates the extent to which the dynamic data deviates from its own mean value over multiple journeys. A discrepancy is typically observed between the dynamic and consistency data, which reflects inconsistencies between the measurement methods and the recorded data from the 3D scan. However, these are evaluated with the utmost precision for the purpose of measurement and are therefore employed as a reference value.

In order to ensure an adequately precise projection, it is essential that the projection distance is below the dynamic measurement threshold. This is because the actual system must also be capable of functioning with deviations up to this distance. Accordingly, a reference value of ± 60 mm is employed for the tests conducted with the ultrasonic system. Should the camera system, which has already been presented as the superior system in [23], achieve real-time capability, the tools listed in 3 will be employed in conjunction with the camera system.

To conduct the experiment, the vehicle is positioned at various points within the test field and replicated in the digital twin. Figure 7 provides a visual representation of the test setup. The measurement at position (1830 mm | 460 mm) yields the values presented in Table 2. The results obtained are supported by tests conducted at other positions in the laboratory.

The data presented in Table 2 illustrates that the initial requirement is largely satisfied. In the case of the beacon pair 9–15, however, there is a value that is 5 mm above the target value, which could be considered an outlier. It is evident that the discrepancy between the physical and digital image intensifies with increasing distance. The results obtained are deemed to be sufficiently accurate for the subsequent procedure.

Moreover, preliminary visualizations of the simulated sensor data can be conducted. The use of an ultrasonic sensor as the fallback level for the ATO system serves to avoid serious collisions. However, due to the functional principle and the cone-shaped detection volume, it is not always evident which obstacle is currently being detected. The visualization of the cone volume for different emergency braking distances facilitates comprehension of the situation (Fig. 8). Furthermore, it facilitates the advancement of the emergency

Table 2 Measurements comparison between physical and digital twin

Beacon Pairs	2–15	2–19	3–15	3–19	9–15	9–19
Digital twin simulation UE5						
Mean distance [mm]	2261,3	2053,7	3816,7	3698,7	5164,0	5353,7
Physical measurement marvelmind dashboard						
Mean distance [mm]	2296,0	2090,7	3862,7	3745,0	5229,0	5408,7
Difference between digital and physical measurement						
Deviation [mm]	34,7	37,0	46,0	46,3	**65,0**	55,0

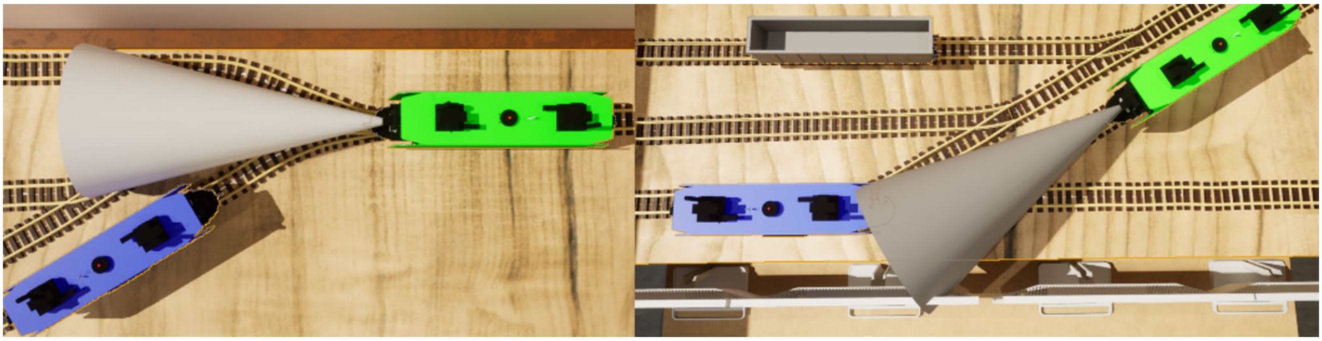

Fig. 8 Analysis of the ultrasonic sensors FoV in different scenarios

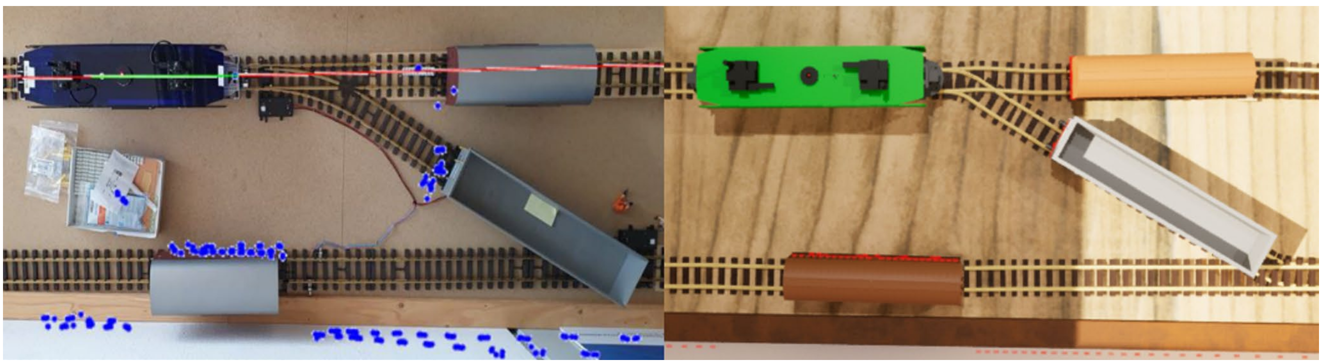

Fig. 9 Qualitative comparison of LiDAR Data (left side real/blue, right side simulated/red)

brake assistant functionality. As illustrated, the utilisation of the ultrasonic sensor does not yield reliable outcomes in the context of tight curve radii. Furthermore, although the system responds to the braking event depicted on the right, it is unclear whether emergency braking is initiated due to the screen or the detected obstacle (locomotive 2).

In the final stage of the process, the analysis of the emulated LiDAR data is prepared. In order to achieve this, the extant LiDAR simulation model is executed with the parameters of the RPLIDAR M2A8, specifically in regard to field of view (FoV) and angular resolution. The results are presented in the qualitative analysis, as illustrated in Fig. 9.

The quantitative analysis yields encouraging outcomes with respect to a real-time, one-to-one comparison of the data. As the one-layer LiDAR is already obsolete at this juncture, as previously outlined in Chap. 3, this phase will be deferred to a subsequent research project. In lieu of this, the search for a new sensor is conducted on the foundation of the digital twin. The straightforward parameterisation of the LiDAR simulation allows for the assessment of the suitability of various LiDAR models with regard to their compatibility with the installation space, thus saving time. As previously stated, the Unitree 4D- LiDAR L1 PM will be employed in the future. A comparative analysis between the RPLIDAR M2A8 and the Unitree 4d- LiDAR l1 PM, conducted through simulation, is presented in Fig. 10.

The selection of the LiDAR module with the digital twin has the potential to significantly enhance the capabilities of the test setup with regard to object detection using LiDAR, as well as the detection of smaller objects in the track bed. This paves the way for a multitude of further research avenues in the scaled model, with the aim of further optimising ATO functions.

Beyond the evaluation of positioning accuracy, temporal synchronization between real and virtual sensor data plays a decisive role. An essential aspect for the meaningful use of the digital twin is the synchronization between real-world data and the virtual environment. For fundamental investigations of sensor simulation, static tests are preferred, as temporal deviations play only a minor role. However, this limits the applicability of the results. In dynamic tests, more extensive investigations are required. The digital twin in UE5 operates at approximately 60 Hz, while the Marvelmind system provides data at 80 Hz with a latency of around 200 ms, LiDAR and camera sensors operate at lower effective rates. As a consequence, the demonstrator vehicle is moved within the environment at a higher temporal resolution than the sensors deliver data, which results in only a local offset caused by latencies. In the current experiments this effect has proven sufficiently small, but at higher velocities or accelerations negative impacts can be expected. One potential mitigation strategy is to employ prediction models

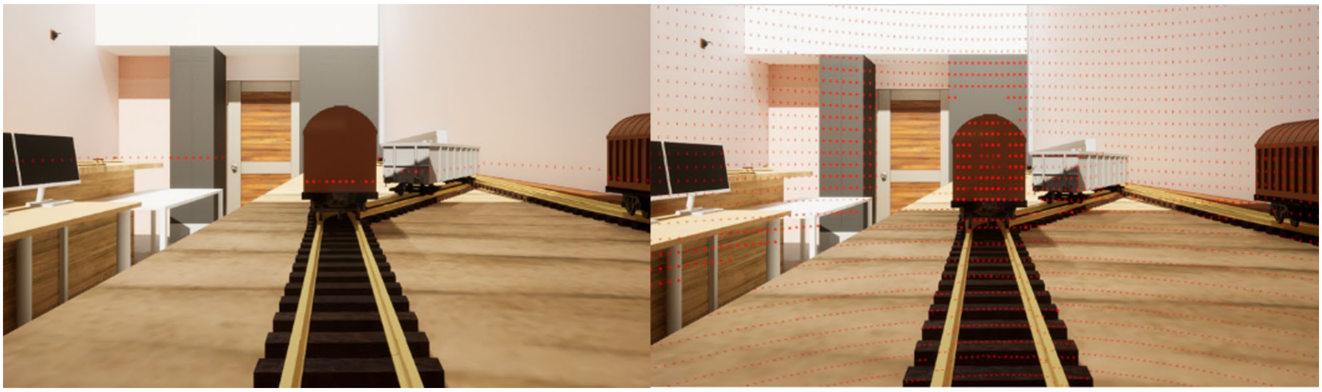

Fig. 10 Virtual Comparison (idealized pointcloud), RPLIDAR M2A8(left), Unitree 4d- LiDAR l1 PM (right, stacked pointcloud)

that place the vehicle "virtually ahead" of its measured position, thus compensating for latency effects.

Furthermore, illumination has proven to be a critical boundary condition for optical sensor systems, particularly cameras. In [39], the influence of ambient lighting on camera-based rail detection in a scaled model environment was systematically investigated using a Design-of-Experiments approach. The results demonstrate that even under laboratory conditions, moderate variations in illumination have significant effects on detection performance, affecting both edge-based rail recognition and camera pose estimation. While static tests primarily allow for qualitative assessment, the findings underline that reproducing realistic lighting conditions for optical sensors within a digital twin remains a major challenge.

Conclusion

The research presented in this paper underscores the significant potential of using scaled models for the development and testing of on-sight ATO systems, particularly in environments without external protection. By addressing the challenges of high costs and limited availability of full-scale test environments, the scaled model approach offers a practical and cost-effective alternative for advancing ATO technologies.

The implementation of object detection using LiDAR sensors within the scaled model successfully demonstrated real-time obstacle detection, closely replicating the capabilities of full-scale systems. The combination of ultrasonic sensors, a camera-based approach, and the use of a digital twin constructed in UE5, provided a comprehensive and accurate platform for testing localization and other critical ATO functions.

The development of a digital twin not only enabled precise simulations but also allowed for real-time comparisons between simulated and real-world sensor data. This ability to validate virtual models against physical counterparts represents a crucial step forward in the iterative development process, offering insights that are often difficult or impossible to obtain from physical testing alone. The qualitative and quantitative analyses, particularly concerning the LiDAR data, demonstrated the utility of the digital twin in evaluating and selecting appropriate sensor systems, such as the transition from the RPLIDAR M2A8 to the Unitree 4D-LiDAR L1 PM.

However, the study also highlights several areas requiring further exploration and improvement. The precision of localization, while generally acceptable, exhibited deviations that warrant closer investigation, particularly as the distance between beacons increased. Additionally, the real-time processing limitations of the camera-based localization system must be addressed to enhance its viability for real-world applications.

Future work should focus on refining the digital twin's accuracy, particularly in terms of integrating more sophisticated sensor models that better account for environmental variables such as weather conditions and material properties. Moreover, the development of more robust algorithms for real-time data processing within the digital twin could bridge the gap between simulation and physical testing even further.

Beyond the comparison of real and virtual datasets, the synchronization between the physical environment and the digital twin also enables the replacement or augmentation of individual sensor data streams. This opens up the possibility of embedding critical situations into real-world datasets based on virtual events generated within the digital twin. In this way, sensor manipulations and sudden, otherwise unrealistic changes can be systematically introduced and evaluated. Such an approach allows safety-critical or hazardous test scenarios to be shifted from the physical domain into the simulation, thereby supporting robustness assessment while reducing risks and resource requirements in real-world testing.

In conclusion, while the scaled model approach has proven to be a valuable tool for ATO development, its full potential has yet to be realized. Continued refinement of both the physical and digital components, along with the integration of more advanced sensor technologies, will be essential for optimizing ATO systems. This research lays a solid foundation for future innovations in railway automation, offering a pathway to more efficient, cost-effective, and safe rail operations.

Further Statements.

Author Contributions Tobias Hofmeier: principal author. Martin Cichon: academic supervision.

Funding Open Access funding enabled and organized by Projekt DEAL. Not applicable—the study didn't involve any 3rd party funding.

Data Availability Not applicable—all relevant data is provided within the document.

Declarations

Conflict of interest Not applicable—the authors declare that they have no conflict of interest.

Research Involving Human and /or Animals Not applicable—no humans or animals were involved.

Informed Consent Not Applicable.

References

1. Kaack LH, Vasihnav P, Morgan MG, Azevedo IL, Rai S. Decarbonizing intraregional freight systems with a focus on modal shift. Environ Res Lett. 2018. https://doi.org/10.1088/1748-9326/aad56c.
2. Trepáčová M, Kurečková V, Zámečník P, Řezáč P. Advantages and disadvantages of rail transportation as perceived by passengers: A qualitative and quantitative study in the Czech Republic, Trans. Transp. Sci. 2020;11(3): 52–62. https://doi.org/10.5507/tots.2020.014
3. Guglielminetti P et al. Study on Single Wagonload Traffic in Europe—challenges, prospects and policy options. Accessed: Jan. 09, 2024. [Online]. Available: https://transport.ec.europa.eu/system/files/2017-02/2015-07-swl-final-report.pdf
4. Pourian TN, effects of automation in railway on the capacity -at the example of the S-BAHN STUTTGART. Accessed: Jan. 10, 2024. [Online]. Available: https://www.diva-portal.org/smash/get/diva2:1777801/FULLTEXT01.pdf
5. Union E. Digitalisation in railway transport, 2019, [Online]. Available: https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/635528/EPRS_BRI(2019)635528_EN.pdf
6. IEC. IEC 62290-1:2006 Railway applications – urban guided transport management and command/control systems – part 1: system principles and fundamental concepts, IEC 62290–1, 2006.
7. Powell JP, Fraszczyk A, Cheong CN, Yeung HK. Potential benefits and Obstacles of implementing driverless train operation on the Tyne and wear metro: a simulation exercise. Urban Rail Transit.2016;2:3–4. https://doi.org/10.1007/s40864-016-0046-9.
8. Zasiadko. Fully automated metros run in six EU countries, RailTech.com. Accessed: Jan. 10, 2024. [Online]. Available: https://www.railtech.com/infrastructure/2019/11/19/fully-automated-metros-run-in-six-eu-countries/
9. Systemtechnik DB. Digitale S-Bahn Hamburg—a safety concept to operate ATO over ETCS. Accessed: Jan. 15, 2024. [Online]. Available: https://www.era.europa.eu/system/files/2022-11/control_major_risks_-_marc.pdf
10. Tinto R. Rio Tinto completes first fully autonomous rail journey in Western Australia. Accessed: Apr. 06, 2023. [Online]. Available: https://www.riotinto.com/en/news/releases/2019/autohaul-successfully- deployed
11. Pachl J. Railway signalling principles. Universitätsbibliothek Braunschweig. 2020. https://doi.org/10.24355/DBBS.084-202006161443-0.
12. Schnieder L. European train control system (ETCS). Berlin, Heidelberg: Springer Berlin Heidelberg; 2021. https://doi.org/10.1007/978-3-662-62878-2.
13. European Commission. State of play - European Commission. Accessed: Jan. 15, 2024. [Online]. Available: https://transport.ec.europa.eu/transport-modes/rail/ertms/state-play_en
14. Tagiew R, et al. Onboard sensor systems for automatic train operation. In: Marrone S, De Sanctis M, Kocsis I, Adler R, Hawkins R, Schleiß P, Marrone S, Nardone R, Flammini F, Vittorini V, editors. in Dependable Computing – EDCC 2022 workshops. Cham: Springer International Publishing; 2022. pp. 139–50.
15. Pegasus PEGASUS. Method: An Overview, Jan. 2019. [Online]. Available: https://www.pegasusprojekt.de/files/tmpl/Pegasus-Abschlussveranstaltung/PEGASUS-Gesamtmethode.pdf
16. Greiner-Fuchs L, Schäfer S, Hofmeier T, Cichon M. Database-supported methodical approach for the development of a toolchain for the evaluation of ATO functions using a scenario-based test methodology. In: Proceedings of the Fifth International Conference on Railway Technology: Research, Development and Maintenance, in Paper 13.4. Montpellier: Civil-Comp Press, 2022. https://doi.org/10.4203/ccc.1.13.4
17. Greiner-Fuchs L, Schäfer S, Hofmeier T, Cichon M. 7-Layer Shunting Model: Generische Szenariobeschreibung automatisierter Rangierfunktionen. In: Proceedings of the 4th International Railway Symposium Aachen 2023, Aachen. 2023. https://doi.org/10.18154/RWTH-2024-00257
18. Schäfer S, Greiner-Fuchs L, Hofmeier T, Cichon M. Entwicklung eines echtzeitfähigen virtuellen Laborprüfstands (Simulationsumgebung) für das szenariobasierte Testen und Validieren hochautomatisierter Fahrentscheidungs-und Steuerungssysteme von Rangierlokomotiven. In: Tagungsband 19. Internationale Schienenfahrzeugtagung Dresden, 2023. p. 108.
19. Hofmeier T, Cichon MG. Introducing scaled model development to on-sight automatic train operation. In: Proceedings of the 10th International Conference on Vehicle Technology and Intelligent

Transport Systems, SciTePress, 2024, pp. 378–385. https://doi.org/10.5220/0012691500003702
20. Aceituno JF, Chamorro R, García-Vallejo D, Escalona JL. On the design of a scaled railroad vehicle for the validation of computational models. Mech Mach Theory. 2017;115:60–76. https://doi.org/10.1016/j.mechmachtheory.2017.04.015.
21. Dresden TU. The Laboratory, TU Dresden. Accessed: Jan. 18, 2024. [Online]. Available: https://tu-dresden.de/bu/verkehr/ibv/ebl/das-labor/startseite?set_language=en
22. Aachen RWTH. Die Eisenbahntechnische Lehr- Versuchsanlage der RWTH Aachen. [Online]. Available: https://www.via.rwth-aachen.de/elva.php
23. Hofmeier T, Kleinlein M, Cichon M. Development of Positioning Methods for ATO in a Scaled Model Environment. In: Proceedings of the Sixth International Conference on Railway Technology Research, Development and Maintenance, J. Pombo, Ed., in Online volume CCC 7. Civil-Comp Press, Edinburgh. 2024, p. Paper 21.1.10.4203ccc.7.21.1
24. Hofmeier T, Greiner-Fuchs L, Schäfer S, Cichon M. Task analysis of a shunting locomotive to derive use-cases for scenario based tests of ATO Functions, presented at the 9th Auto Test Conference, Stuttgart. 2022. [Online]. Available: https://www.researchgate.net/publication/364301750
25. Hofmeier T, Cichon M. A Scaled Lab Proposal for Development and Testing of On-Sight Automatic Train Operation. Accessed: Jul. 02, 2025. [Online]. Available: https://www.researchgate.net/publication/393267484
26. Rückert FU, Sauer M. Die erstellung eines digitalen Zwillings. Wiesbaden: Springer Fachmedien; 2021.
27. Krmac E, Djordjevic B. Digital twins for railway sector: current state and future directions. IEEE Access. 2024;12:108597–615. https://doi.org/10.1109/ACCESS.2024.3439471.
28. Zhou M, Hou Z, Liu J, Reborts C, Dong H, Digital Twin-based Automatic Train Regulation for Integration of Dispatching and Control. In: 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI). 2021. pp. 461–464. https://doi.org/10.1109/DTPI52967.2021.9540141
29. Tang Z, Ling L, Zhang T, Hu Y, Wang K, Zhai W. Towards digital twin trains: implementing a cloud-based framework for railway vehicle dynamics simulation. Int J Rail Transp. 2025;13(3):444–67. https://doi.org/10.1080/23248378.2024.2355578.
30. Padovano A, Longo F, Manca L, Grugni R. Improving safety management in railway stations through a simulation-based digital twin approach. Comput Ind Eng. 2024;187:109839. https://doi.org/10.1016/j.cie.2023.109839.
31. Schäfer S, Yöndem FS, Aliziyad MINM, Cichon M. Virtual Reality and Digital System Twins in the Development and Testing of Trainable Highly Automated Driving Decision Making in Shunting Operations. In: RSA 2023: Tagungsband/proceedings: Aachen, Germany 22–23 November 2023, Ed.: Nießen, Nils ; Schindler, Christian, 4th International Railway Symposium Aachen (IRSA 2023), Aachen, Deutschland, 22.11.2023–23.11.2023, RWTH Aachen University. 2024. pp. 726–746.
32. BayernAtlas. bayernatlas.de. Accessed: Sep. 04, 2024. [Online]. Available: https://www.bayernatlas.de
33. Unreal Engine Documentation, Unreal Engine. Accessed: Sep. 04, 2024. [Online]. Available: https://www.unrealengine.com/en-US/home
34. BRouter. Web Client. Accessed: Sep. 04, 2024. [Online]. Available: https://brouter.de/brouter-web/#map=15/48.1950/11.4816/osm-mapnik-german_style&profile=rail
35. OpenRailwayMap. Accessed. Sep. 04, 2024. [Online]. Available: https://www.openrailwaymap.org/
36. Muckenhuber S, Holzer H, Bockaj Z. Automotive lidar modelling approach based on material properties and lidar capabilities. Sensors. 2020;20(03309):1–25. https://doi.org/10.3390/s2003309.
37. Manivasagam S et al. LiDARsim: realistic LiDAR simulation by leveraging the real world. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 2020. pp. 11167–11176.
38. Espineira JP, Robinson J, Groenewald J, Chan PH, Donzella V. Realistic lidar with noise model for real-time testing of automated vehicles in a virtual environment. IEEE Sens J. 2021;21:9919–26.
39. Hofmeier T, Otto K, Cao Y, Cichon M. Vorentwicklung kamerabasierter on- sight-ATO-Funktionen -Schienenkopf- und Weichenlagendetektion sowie infrastrukturseitige Unterstützung der Lichtraumprofilüberwachung bei geschobenen Einheiten im skalierten Modell. [Online]. Available: https://www.researchgate.net/publication/395016279