Rail to Digital Automated up to autonomous Train Operation

D7.3 – Perform simulation with initial implementation of the Data Factory

Due date of deliverable: 30/09/2024
Actual submission date: 01/09/2025

Leader/Responsible of this Deliverable: Dr. Philipp Neumaier | DB InfraGO AG

Reviewed: Y

Document status		
Revision	Date	Description
01	21/08/2024	Intermediate Version of documentation shared with Partners
02	01/09/2024	TMT-ready Version
03	27/01/2025	Figures 1,2,3 & 9 have been exchanged for higher resolution versions
04	01/09/2025	Table borders changed
05	15/10/2025	Formatting adjusted to comply with the standard template (Arial, font size 11); corrected title spacing; updated heading styles; fixed figure numbering (37 figures total); removed incorrect comment; restored original section numbering (Introduction as Section 1)

Project funded from the European Union's Horizon Europe research and innovation programme		
Dissemination Level		
PU	Public	X
CO	Confidential, restricted under conditions set out in Model Grant Agreement	

Start date: 01/12/2022 Duration: 22 months

ACKNOWLEDGEMENTS

This project has received funding from the Europe's Rail Joint Undertaking (ERJU) under the Grant Agreement no. 101102001. The JU receives support from the European Union's Horizon Europe research and innovation programme and the Europe's Rail JU members other than the Union.

REPORT CONTRIBUTORS

Name	Company	Details of Contribution
Dr. Philipp Neumaier	DB	Content creator
David Garcia Olivares	DB	Content creator
Christian C Buchta	DB	Content creator
Koraltan Kaynak	DB	Content creator
Patrick Denzler	DB	Content creator
Sebastian Dubiel	DB	Content creator
Cedrick Lelionnais	SNCF	Content creator
Philippe Bourdenet	SNCF	Content creator
Philippe David	SNCF	Content creator
Bastian Simoni	Alstom	Expert Review
Dominik Kevicky	AZD	Expert Review
Frederic Antoine	ATSA	Expert Review
Hardik Jain	THD/Thales	Expert Review
Hájek Jiří	AZD	Expert Review
Lars Bergmann	Siemens	Expert Review
Lars-Kristian Vognild	NRD	Expert Review
Maik Baehr	Siemens	Expert Review
Michal Novak	AZD	Expert Review
Michele Bruzzo	Hitachi	Expert Review
Dr. Oliver Lehmann	SMO	Expert Review
Saro Thiyagarajan	FT/Wabtec	Expert Review
Sebastiaan Linssen	NS	Expert Review
Tom Jansen	NS	Expert Review

Disclaimer

The information in this document is provided "as is", and no guarantee or warranty is given that the information is fit for any particular purpose. The content of this document reflects only the author's view – the Joint Undertaking is not responsible for any use that may be made of the information it contains. The users use the information at their sole risk and liability.

EXECUTIVE SUMMARY

CONTEXT AND OBJECTIVES

The ongoing digitalization and automation within the European railway sector are important to enhancing operational efficiency, safety, and sustainability, which are needed to meet the increasing demands of modern transportation. The R2DATO project is a key initiative aimed at developing Next-Generation Automatic Train Control (ATC) systems, ultimately enabling autonomous train operations across Europe. Deliverable 7.3, titled " Perform Simulation with Initial Implementation of the Data Factory", is a cornerstone of this effort. It addresses the critical need to generate synthetic sensor data through advanced simulations, a task essential for the training and validation of machine learning models used in autonomous systems. The primary objectives of this deliverable were to create a robust simulation framework that integrates the needs and requirements of key stakeholders, to model a variety of railway scenarios—both regular and non-regular—and to produce synthetic data that closely mirrors potential real-world conditions.

The scope of D7.3 was comprehensive, involving collaboration between Deutsche Bahn (DB) and SNCF, two of Europe's leading railway operators. The deliverable was tasked with bridging the gap between theoretical concepts outlined in previous deliverables, particularly D7.1, and practical implementation. This involved not only developing the simulation environment but also ensuring it could meet the diverse needs of the stakeholders involved, including requirements for the D7.6 Open Dataset. This dataset will serve as a vital resource for training and testing AI models, particularly in scenarios that are too dangerous or rare to replicate in real life.

SCIENTIFIC/TECHNICAL APPROACH

The scientific and technical approach taken in D7.3 was both innovative and collaborative, involving significant contributions from DB and SNCF. The project began by conducting an extensive review of existing simulation frameworks and identifying gaps that needed to be addressed. The team then focused on developing an advanced simulation environment that could accurately model both regular operational scenarios and more complex Non-Regular Situations (NRS), such as those involving accidents or other rare but critical events.

A key aspect of this approach was the creation of high-fidelity 3D models of trains, incorporating detailed sensor placements to ensure precise data collection. Given the complexity of accurately replicating dynamic elements, the project initially focused on static scenarios, where the sensor setup and environmental conditions could be controlled and analysed with high precision. This included the strategic placement of sensors on models like the French Train (SNCF B82500), as well as the simulation of various static obstacles to test the platform's robustness in generating relevant sensor data. Despite the focus on static objects, the synthetic data produced was of high quality and relevance, laying the groundwork for its application in model training and validation.

The project also dealt with the significant challenge of balancing simulation detail with computational resources. High-detail simulations require substantial processing power and time, which were managed by optimizing sensor resolutions and data processing techniques. This ensured that the simulations remained efficient while still producing data that met the necessary precision standards for further use.

MAIN FINDINGS AND CONCLUSIONS

The simulations conducted under D7.3 successfully demonstrated the feasibility and effectiveness of the simulation platform, which was initially conceptualized in D7.1. The project achieved significant milestones, including the successful integration of diverse stakeholder requirements into a functional simulation system. This accomplishment validated the real-world applicability of the platform, proving that it can execute complex simulations that are critical for the project's broader objectives.

One of the most significant outcomes of D7.3 was the generation of synthesized data, which is an essential component of the D7.6 Open Dataset. This data serves as a reliable substitute for real-world data, particularly in training AI models on scenarios that are too dangerous or infrequent to capture in reality. For instance, the data includes simulations of Non-Regular Situations (NRS) such as accidents, which are rare but vital for preparing AI models to handle potential real-world dangers. The ability to simulate these scenarios is crucial, as it allows for the creation of large volumes of training data necessary for the development and homologation of AI systems. This process ensures that AI models are rigorously tested and qualified for real-world deployment, thus accelerating the development and adoption of autonomous technologies in the rail sector.

However, the project also faced several challenges and limitations. One of the key challenges was the trade-off between the level of simulation detail and the available computational resources. To manage this, the team had to make compromises, such as reducing sensor resolution to decrease data size and processing time. While these compromises were necessary, they also highlighted the limitations of the current system, particularly in terms of simulating dynamic objects and fully replicating real-world sensor setups. These challenges underscore the need for further refinement and development in future stages of the project.

Despite these challenges, the findings from D7.3 indicate that the simulation platform is highly capable of producing reliable and relevant synthetic data. This data will be instrumental in the subsequent phases of the project, particularly in training and testing machine learning models that are central to the development of autonomous train systems.

RECOMMENDATIONS FOR FUTURE WORK

Building on the successes of D7.3, several areas have been identified for further research and development. A primary recommendation is to enhance the simulation platform by incorporating dynamic objects, which would significantly broaden the scope and applicability of the synthetic data. This is particularly important for scenarios involving moving trains, dynamic obstacles, and interactions that are critical for the accurate training of AI models.

Another crucial next step is the validation of the synthesized data against real-world data. This will require the development of specific metrics and methodologies to assess the accuracy and fidelity of the simulation data. Such validation is essential to ensure that the synthetic data can be reliably used in place of real-world data for training and testing AI models. Additionally, future work should focus on expanding the simulation capabilities to include more detailed environmental conditions, such as the effects of rain, fog, and other weather phenomena on sensor performance. These enhancements will make the simulations more realistic and applicable to a wider range of real-world scenarios.

The business model for offering simulations and synthetic data within the rail sector is also an area of focus for future development. DB InfraGO AG is currently developing a simulation platform that could be offered to other stakeholders in the rail industry. This platform would allow for the generation and sharing of synthetic data, particularly from Non-Regular Situations, thereby creating new opportunities for collaboration and innovation within the sector.

Finally, the project should consider establishing a sector-wide initiative for joint simulations. Such an initiative could leverage the collective expertise and resources of various stakeholders to accelerate the development and refinement of simulation technologies. This would not only benefit the R2DATO project but also contribute to the broader goal of advancing digitalization and automation within the European rail industry.

ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
API	Application Programming Interface
ATC	Automatic Train Control
ATO	Automatic Train Operation
CUT	Contrastive Unpaired Translation
DB	Deutsche Bahn
DDP	Distributed Data Parallel
Dx.x	Deliverable x.x
FPS	Frames per Second
GAN	Generative Adversarial Network
GPU	Graphics Processing Unit
HDR	High Dynamic Range
IMU	Inertial Measurement Unit
IMX490	Kamerasensor von Sony
LiDAR	Light Detection and Ranging
mAP	Mean Average Precision
ML	Machine Learning
MUNIT	Multimodal Unsupervised Image-to-Image Translation
NIR	Near Infrared
NRS	Non-Regular Situations
OVX	NVIDIA-Plattform für Simulationen
R2DATO	Rail to Digital Automated up to Autonomous Train Operation
ROS	Robot Operating System
S-Bahn	Schnellbahn
SNCF	Société Nationale des Chemins de fer Français
UNIT	Unsupervised Image-to-Image Translation Networks
USD	Universal Scene Description
WP	Work Package

TABLE OF CONTENT

LISTS OF FIGURES

LISTS OF TABLES

1 INTRODUCTION

1.1 PURPOSE OF THE DOCUMENT

The purpose of this document is to report on the progress and outcomes of Deliverable D7.3 of Work Package 7 within the R2DATO project, specifically focusing on the initial simulations performed with the Data Factory prototype. The deliverable serves to provide an in-depth analysis of the methodologies applied during the simulations, the types of data generated, and the preliminary findings that will inform subsequent project activities. This document also aims to highlight the potential improvements and further developments required to enhance the Data Factory's capability in generating high-quality synthetic sensor data for machine learning (ML) and artificial intelligence (AI) model training. Furthermore, it will serve as a foundation for the upcoming deliverables, particularly D7.5 and D7.6, which are critical for the advancement of the project's objectives.

1.2 SCOPE OF THE DELIVERABLE

The scope of Deliverable D7.3, as defined in the Grant Agreement, encompasses the execution and analysis of initial simulations using the Data Factory prototype developed in Task 7.2. This deliverable is intrinsically linked to the broader objectives of Work Package 7 (WP7) and serves as a precursor to the subsequent tasks and deliverables. Specifically, D7.3:

- Supports the further development of the Data Factory, ensuring it meets the requirements for effective ML/AI training and the eventual release of an Open-Dataset in D7.6.
- Provides critical data and insights that will be utilized in Deliverable D7.5 for the training of ML/AI models.
- Establishes a foundation for data annotation processes that will be fully realized in Deliverable D7.4.
- Informs the ongoing refinement and validation of the Data Factory, contributing to its readiness for large-scale deployment within the project.

This deliverable is important in setting the stage for the realization of WP7's goals, specifically by enabling the production of synthetic sensor data that will be instrumental in achieving high fidelity and robust ML/AI models for railway operations.

1.3 DOCUMENT STRUCTURE

The document is structured into several comprehensive sections, each designed to cover different aspects of Deliverable D7.3:

- **Executive Summary**: A concise overview of the deliverable's objectives and key findings, providing readers with a quick understanding of the document's purpose and outcomes.
- **Introduction**: This section outlines the purpose of the document, the scope of the deliverable, and the structure of the document itself, including definitions and abbreviations used throughout.
- **Project Overview**: Provides background information on the R2DATO project, detailing its objectives and identifying the stakeholders and their responsibilities.

- **Simulation Framework**: Describes the setup of the simulation environment, including the software tools used and how these tools integrate with other systems within the project.
- **Modeling and Assets**: Discusses the 3D modeling work, including enhancements to train models and the creation of various simulation assets like Non-Regular Situation (NRS) obstacles.
- **Simulation Scenarios**: Defines the locations and scenarios used in the simulations, both regular and non-regular, and explains the process for selecting these scenarios.
- **Sensor Data and Simulation**: Focuses on the types of sensors used, their placement, configuration, and how the sensor data is synchronized and processed during simulations.
- **Simulation Execution**: Details the preparation, execution of simulation runs, and how the data and video outputs are recorded.
- **Prospective View on Enhancing Simulation Imagery with Neural Networks:** Explores the application of AI and neural networks to enhance simulation imagery, including discussions on simulation assets, objectives, and technical processes.
- **Results and Discussion**: Presents the findings from the simulations, discusses their implications, and outlines the challenges encountered, along with recommendations for future work.
- **Conclusion**: Summarizes the achievements of the deliverable and its contribution to the overall project goals.
- **References**: Lists the bibliographical sources and literature cited throughout the document.

1.4 Definitions and Abbreviations

This section provides a list of key terms, acronyms, and abbreviations used throughout the document. It ensures that all readers, regardless of their familiarity with the specific terminology of the R2DATO project, can fully understand the content. Definitions are provided for technical terms related to the Data Factory, simulation processes, and any specialized tools or methodologies discussed in the deliverable. By clarifying these terms upfront, this section supports the overall readability and accessibility of the document.

2 PROJECT OVERVIEW

2.1 BACKGROUND INFORMATION

The R2DATO (Rail to Digital and Automated Train Operations) project is a flagship initiative under Europe's Rail Joint Undertaking, aimed at addressing the increasing demand for rail transport of both passengers and freight. The project takes advantage of digitalization and automation to develop the Next Generation Automatic Train Control (ATC) systems, which will deliver scalable automation capabilities up to Autonomous Train Operations (ATO). This approach is crucial in enhancing the capacity of existing rail networks without the need for extensive new infrastructure, which is often expensive and time-consuming to implement.

The project aligns with the European Commission's Green Deal objectives, which emphasize decarbonization and the transition to a more efficient and sustainable transport system. R2DATO contributes to these goals by improving the punctuality, reliability, and productivity of rail transport, ultimately supporting a modal shift from road to rail and increasing the competitiveness of the European rail industry.

2.2 PROJECT OBJECTIVES

The primary objective of the R2DATO project is to harness digital technologies and automation to transform Europe's rail system into a more efficient, sustainable, and competitive mode of transportation. The project sets out to achieve several specific objectives, including:

- Development of Next-Generation ATC: Creating scalable automation solutions up to GoA4 (Grade of Automation level 4), which allows for fully autonomous train operations across different segments, including freight and urban light rail.
- Enhancing Infrastructure Capacity: By implementing advanced automation technologies, the project aims to significantly increase the capacity of existing rail networks, facilitating the movement of more trains safely and efficiently.
- Supporting the European Green Deal: The project contributes to the EU's environmental goals by reducing carbon emissions, improving energy efficiency, and encouraging a shift from road to rail transport.
- Standardization and Interoperability: R2DATO will develop standards and open interfaces to ensure that the technologies created can be widely adopted across Europe, supporting a harmonized rail system.
- These objectives are designed to ensure that the R2DATO project not only advances technological innovation in the rail sector but also delivers practical, deployable solutions that will benefit the European transport network as a whole.

2.3 Stakeholders and Responsibilities

In Deliverable D7.3, two primary stakeholders are responsible for the successful implementation of joint simulation tasks: SNCF (Société Nationale des Chemins de fer Français) and Deutsche Bahn AG.

SNCF

Role: SNCF is responsible for providing real-world data, simulation assets, and technical expertise necessary for the simulations. Their tasks include supplying detailed 3D models of trains and infrastructure, ensuring that these assets are accurately textured and formatted for use in the simulation environment. Additionally, SNCF defines and validates non-regular situation (NRS) scenarios, such as track obstacles and other unexpected events, for simulation.

Key Responsibilities:

- Supplying 3D models and textures in the required formats (preferably USD) for simulation.
- Defining realistic NRS based on operational data from the French rail network.
- Coordinating the placement and configuration of sensors on the trains used in simulations.
- Ensuring timely delivery of simulation assets and participating in the validation of simulation outcomes.
- Provide a study on using neural networks on 3D simulated images

Deutsche Bahn AG

Role: Deutsche Bahn is responsible for the technical development and execution of simulations within the Data Factory. This involves setting up the simulation environment, integrating the assets provided by SNCF, and conducting the simulations. Deutsche Bahn also handles data processing, analysis, and ensuring that the synthetic data generated meets the project's requirements for machine learning and AI training.

Key Responsibilities:

- Developing and refining the Data Factory infrastructure, both hardware and software-wise to enable simulations.
- Supporting expertise regarding non-regular situations (NRS).
- Modelling of the digital twin of the railway environment (Hamburg).
- Modelling of the physical boundary conditions.
- Integrating SNCF's assets into the digital twin railway environment and ensuring compatibility.
- Executing simulations of railway scenarios and storing, managing and granting access to the synthetic sensor data within large datasets.
- Providing feedback to SNCF on the usability and effectiveness of provided assets and data.

Together, **SNCF** and **Deutsche Bahn** work closely to ensure that simulations are realistic, technically sound, and aligned with the broader objectives of the R2DATO project.

2.4 Overview of Simulation Environment

The simulation environment used for Deliverable D7.3 is designed to accurately replicate real-world railway scenarios, leveraging the Data Factory's capabilities to generate synthetic data for machine learning and AI training. The environment is built using advanced 3D modeling and simulation software, capable of integrating various assets, such as trains, infrastructure, and non-regular situations (NRS). This environment simulates the dynamic interaction between trains and their surroundings, allowing for comprehensive testing and validation of sensor data under controlled conditions.

The environment is based on real-world data provided by SNCF, including detailed 3D models of French trains and railway infrastructure. These models are enhanced with realistic textures and configured to simulate specific operational scenarios, such as obstacle detection and sensor calibration. The simulation is primarily set in a digital twin of the Hamburg railway environment, which has been augmented with additional scenarios and assets to reflect both German and French railway conditions.

2.5 Description of the Simulation Software and Tools

The simulation framework is supported by a range of software tools and platforms, including:

NVIDIA Omniverse Isaac Sim 2022[1]: A key tool used for creating and managing the 3D simulation environment. It allows for the integration of assets in USD format, which is the preferred format due to its comprehensive support for complex geometric and shading attributes. Isaac Sim also focuses on working with sensors, physics, lighting conditions, and materials, providing realistic and accurate simulations. Additionally, Omniverse also supports real-time collaboration and rendering, making it an ideal platform for developing high-fidelity simulations.

ROS 2 (Robot Operating System 2) Humble[2]: This software is used for managing the simulation of perception systems, such as cameras and LiDAR sensors. It provides a framework for capturing and processing sensor data in real-time, which is essential for generating accurate synthetic data that can be used to train AI models.

Foxglove[3]: A software tool used for visualizing and analysing ROS bags, allowing to inspect the data generated by the simulation. It provides an intuitive interface for viewing sensor data, messages, and system states in real-time or from recorded sessions.

Unity 3D[4]: Unity is utilized for certain aspects of 3D modeling and animation, particularly for dynamic assets that require realistic physical interactions, such as collisions between trains and obstacles. Unity’s flexibility allows for detailed control over the behavior of these assets during simulations.

[1] (developer.nvidia.com, 2024)

[2] (docs.ros.org, 2024)

[3] (docs.foxglove.dev, 2024)

[4] (unity3d.com, 2024)

Blender[5]**:** Used for creating and refining 3D models provided by SNCF, particularly in converting these models into the USD format for integration into the simulation environment. Blender's tools are also utilized for texture mapping and model enhancement.

These tools are integrated into a cohesive workflow that supports the end-to-end simulation process, from asset creation and scenario design to real-time simulation and data collection.

2.5.1 Integration with the Data Factory's Simulation Platform

As described in D7.1[6], the Data Factory's Simulation Platform is a critical subsystem that handles the creation, management, and validation of simulation scenarios and 3D assets.

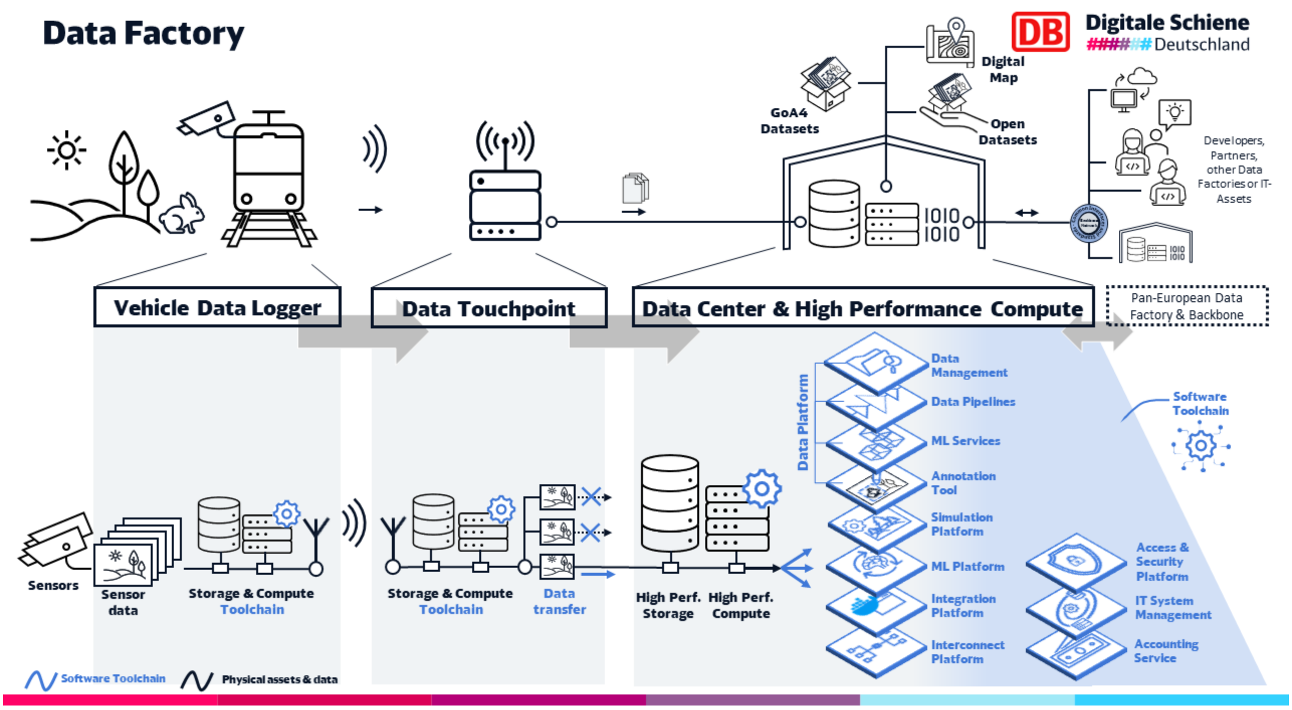


Figure 1: Envisioned Target Architecture of the Data Factory

[5] (developer.blender.org, 2024)

[6] D7.1 – Requirements and specifications for Data Factory

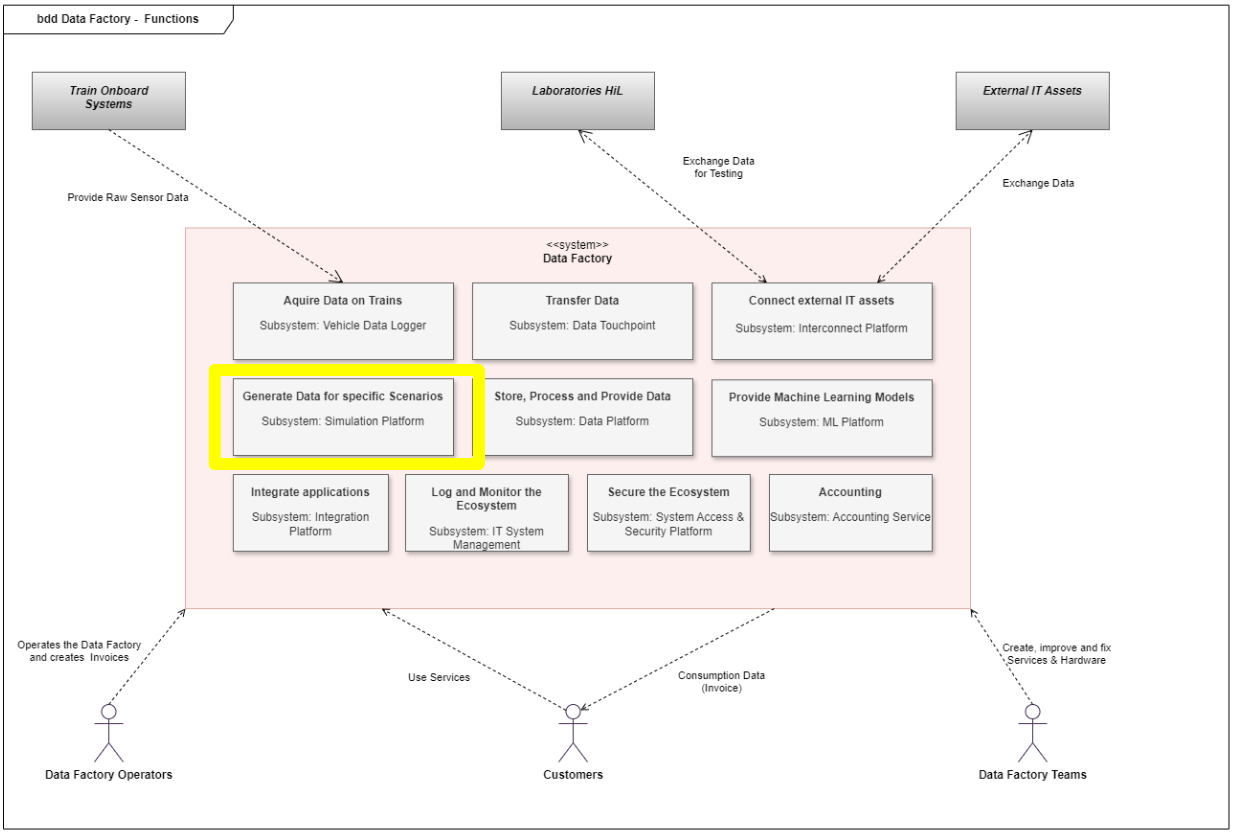


Figure 2: White Box View of the Data Factory

The following Components and Stakeholder are particularly relevant (and part of the Data Factory Teams / Customers):

- **Asset Manager**: Ensures that 3D assets are meticulously created, updated, and validated. It guarantees that the data and integrity of these assets are maintained throughout the simulation process, which is crucial for achieving realistic and accurate results.
- **Scenario Sampler**: Responsible for the detailed preparation and management of simulation scenarios, including versioning and parameter settings. This subsystem is integral to developing diverse and realistic scenarios, which are essential for testing the Data Factory's operations.
- **Generator**: This component drives the creation of synthetic data by simulating scenarios and recording the resulting data streams. The generated synthetic data is then used to train AI models, making it a vital part of the Data Factory's workflow.
- **Validator**: Tasked with validating both digital twins and 3D assets, ensuring that the simulated environments closely mirror their real-world counterparts. This validation process is critical for maintaining the accuracy and reliability of the simulations.

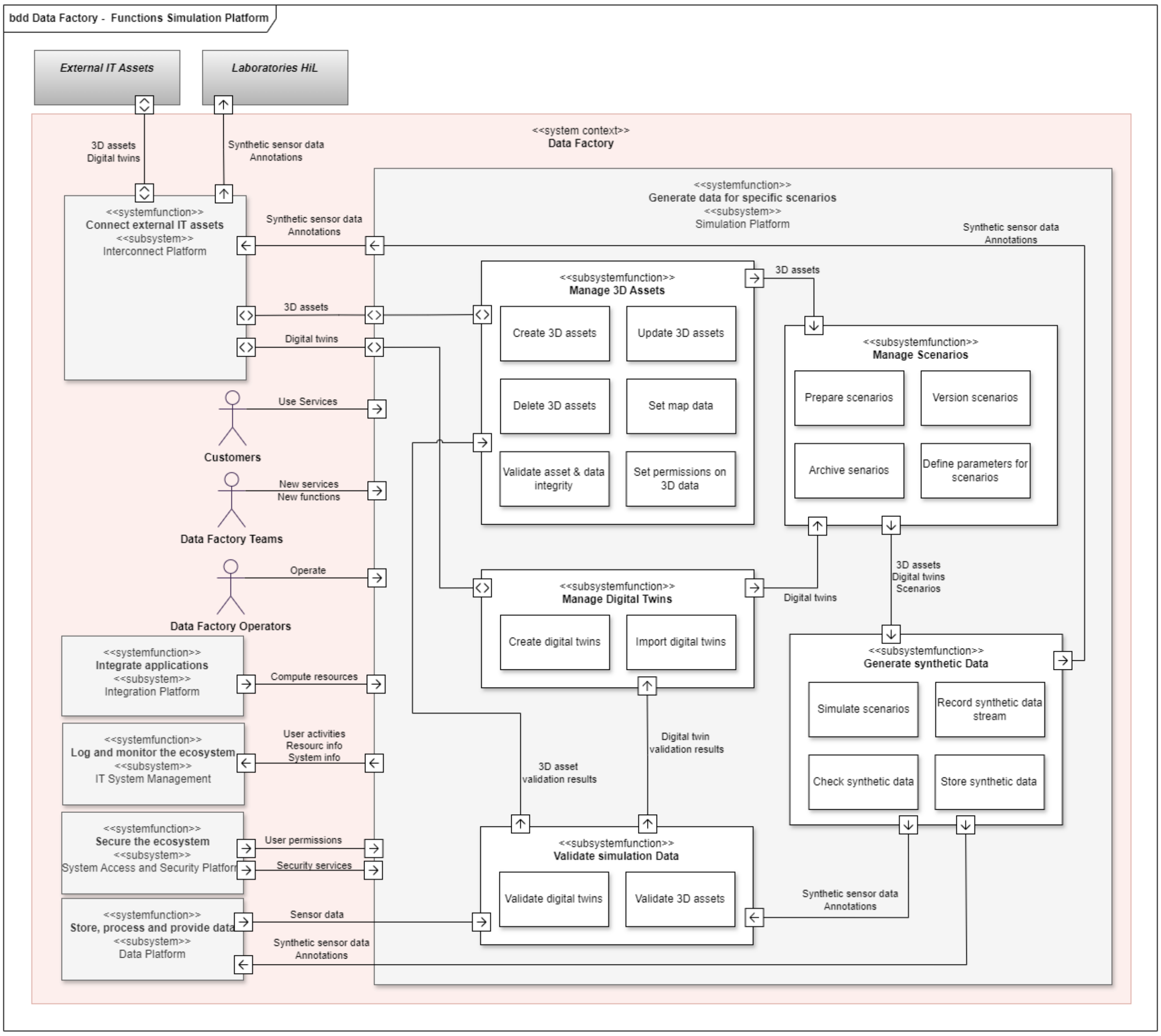


Figure 3 Context diagram Simulation Platform

In summary, the tools and platforms described here are not just for building and running simulations but are deeply integrated into the Data Factory's ecosystem. They contribute to the generation, validation, and refinement of data that is critical for advancing the project's objectives, particularly in the context of GoA4 ATO systems.

2.6 INTEGRATION WITH OTHER SYSTEMS

The simulation environment is designed to integrate seamlessly with other systems within the R2DATO project, particularly those used for data analysis and machine learning model training. Data generated from the simulations, including sensor readings and scenario outcomes, are stored in formats that are compatible with the Data Factory's broader data processing pipeline.

The integration process also involves synchronizing the simulation outputs with real-world data provided by SNCF or DB (or other stakeholders like customers), allowing for a comparison between simulated and actual railway operations. This synchronization is crucial for validating the accuracy and reliability of the synthetic data generated during the simulations.

Additionally, the simulation environment is configured to work alongside other digital twin platforms and data visualization tools, ensuring that all stakeholders have access to the simulation data in formats that are easy to analyze and interpret. This level of integration supports the overall objectives of WP7, facilitating the development of robust AI models that can be deployed in real-world railway environments.

3 MODELING AND ASSETS

3.1 3D MODELING OF TRAINS

3.1.1 French Train Model Enhancement

For the simulations conducted as part of Deliverable D7.3, SNCF provided detailed 3D models of French train SNCF B82500, which were integral to creating realistic simulation scenarios. These models were enhanced with high-resolution textures to ensure that the simulations accurately reflect the physical characteristics of the trains. SNCF worked on improving the visual and structural details of these models, particularly focusing on aspects like the exterior features and sensor placements that are crucial for realistic simulations. These enhancements were critical in achieving a high level of detail, which is necessary for the effective analysis and validation of sensor data during the simulations.

Figure 4 Front View of Enhanced French Train Model

Figure 5 Side View of Enhanced French Train Model

3.1.2 Selected Sensors for Digital Sensor Twins

For multimodality of the synthetic sensor data, three rgb cameras and one Lidar were selected. The selected camera twin is a IMX490 and the Lidar twin is a Ibeo Next 11. Table 1 states the technical properties of both sensor types.

Modality	Sensor ID	Model	Technical Data	
Camera	Cam 1 Cam 2 Cam 3	IMX490	Company Sensor Resolution Lens Colour Depth Frame Rate Focal Length Focus Distance Roll Pitch Yaw	Sony IMX490 1032 (H) × 1544 (V) Fujifilm HF50SA-1 8 bits 30 fps 50 mm 400 cm 0 6° 0
Lidar	Lidar 1	Next 11	Company Model Type Resolution Type Frame Rate Roll Pitch Yaw	IBEO Next 11 1032 (H) × 1544 (V) Solid State 30 fps 0 6° 0

Table 1: Technical information of selected sensors

3.1.3 External Sensor Placement on French Train

The placement of external sensors on the French trains was planned to mirror real-world configurations. This included the strategic positioning of cameras, LiDAR, and other perception systems, which are essential for capturing the environment around the train. The sensors were placed at various points, including on top of the train and at the driver's eye level, to maximize their field of view and accuracy in detecting obstacles. SNCF provided the specifications and technical drawings necessary for positioning these sensors, ensuring that the simulation environment closely replicates actual operational conditions.

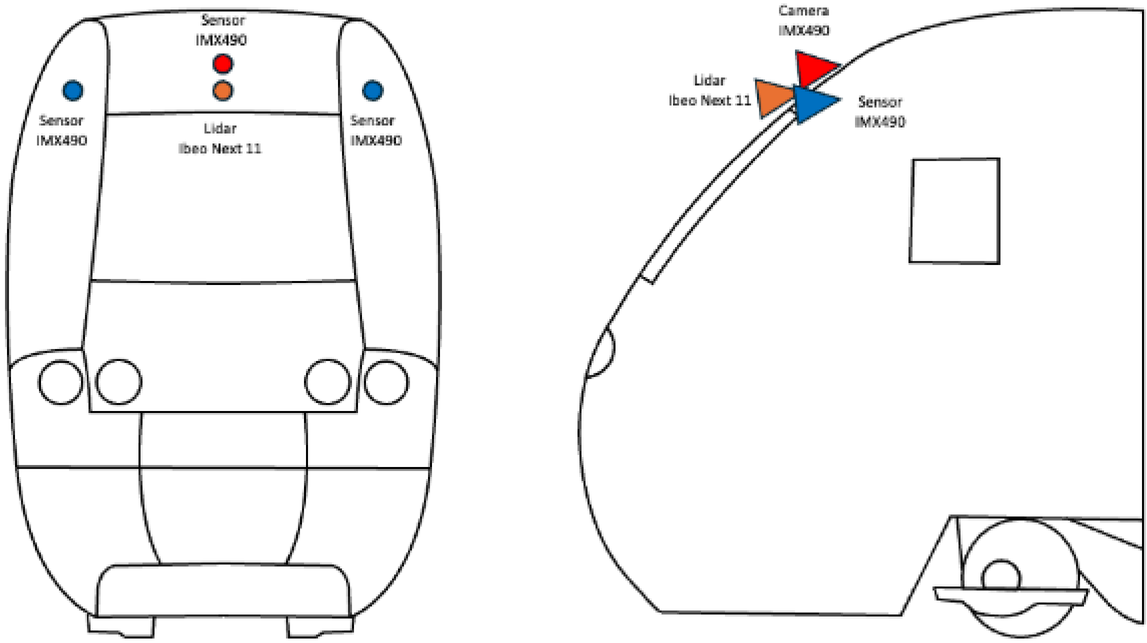


Figure 6 Sensor Placement on French Train Model

3.2 Static Non-Regular Situation (NRS) Obstacles

3.2.1 Textual Description of NRS and Corresponding Real-Life Incidents

Non-Regular Situations (NRS) refer to unexpected obstacles or events that can occur on or near railway tracks, posing significant risks to train operations. The NRS scenarios modelled in the simulations were chosen based on real-world incidents, particularly from the French rail network. These scenarios include both static and dynamic obstacles such as supermarket trolleys on tracks, fallen trees, and debris from unsecured freight. The selection of these scenarios was informed by actual occurrences documented by SNCF, which provided a realistic basis for the simulations. This approach ensured that the simulations would yield valuable insights into how automated systems can detect and respond to such hazards.

Additionally, the provided elements (information, landscape environment, assets) needed to enable developers to create scenarios inspired by the French context. For this reason, the team relied primarily on testimonies from train drivers and incident reports, particularly those maintained by “Transilien” (the SNCF trains serving the Paris region), which serve as an extremely valuable working base.

This report includes various incidents, such as "collisions and impacts," collision risks, or gauge infringements (any action resulting in damage to the train’s exterior, whether by friction or impact from an external object). It compiles observations made by train operators at the end of their shifts to explain or report an incident, or even an accident. From these written descriptions, we were able to categorize our non-regular situations and produce the following list.

3.2.1.1 Category: Static Objects on Track

1. **NRS: Fallen Tree**
   - **Description:** A large tree has fallen onto the tracks, blocking train passage.
   - **Real-Life Incident:** Bad Driburg Derailment (2024) – A tree fell on the tracks, leading to a train derailment.[7]
   - **Scenario Details:** This scenario is suitable for simulating sensor detection of large, stationary obstacles, particularly in adverse weather conditions where such incidents are more likely.
2. **NRS: Supermarket Trolley (chosen for simulation run)**
   - **Description:** A trolley abandoned on the tracks, posing a risk to passing trains.
   - **Real-Life Incident:** Train Collision in Niedersachsen (2022) – On October 23, 2022, a train collided with a supermarket trolley that was left on the tracks.[8]
   - **Scenario Details:** The scenario tests the ability of sensors to detect small but potentially dangerous objects on the tracks, ensuring timely response to avoid accidents.
3. **NRS: Broken Catenary**
   - **Description:** Damaged overhead wires hanging low over the tracks, creating a hazard.
   - **Real-Life Incident:** Infrastructure Failure – This type of incident is common with overhead infrastructure.
   - **Scenario Details:** This scenario simulates the detection of overhead obstacles that could cause significant damage to passing trains, particularly focusing on sensor accuracy and response.
4. **NRS: Forklift Truck on Track**
   - **Description:** A forklift truck left on the tracks, potentially by mistake.
   - **Real-Life Incident:** Freight Train Collision in Karlsbach (2022) – A collision occurred with a maintenance vehicle left on the tracks.[9]
   - **Scenario Details:** This scenario evaluates the sensor's ability to detect unexpected large objects on the tracks during non-operational hours, highlighting the need for vigilance even during maintenance or low-traffic periods.
5. **NRS: Lying Truck (chosen for simulation run)**
   - **Description:** A truck has overturned onto the tracks, posing a significant hazard.
   - **Real-Life Incident:** Berlin Incident (2018) – A train collided with a construction vehicle that had fallen onto the tracks.[10]
   - **Scenario Details:** This scenario simulates the detection of large vehicles on the tracks, requiring an immediate automated response to prevent a serious accident.
6. **NRS: Stones or Rocks (chosen for simulation run)**

[7] (radiohochstift.de, 2024)

[8] (ndr.de, 2022)

[9] (schiene.de, 2022)

[10] (SDA/nag, 2018)

- **Description:** Large rocks or debris have fallen onto the tracks, possibly due to landslides.
- **Real-Life Incident:** Simplon Railway Derailment (2024): On May 5, 2024, a BLS train derailed on its way to Switzerland after colliding with rocks that had fallen onto the tracks.[11]
- **Scenario Details:** The scenario tests the detection of smaller, multiple obstacles, reflecting the complexity and challenges of rural or open track sections where such hazards are more common.

7. **NRS: Euro Pallet on Track**
   - **Description:** A Euro pallet has fallen onto the tracks, creating a significant obstruction.
   - **Real-Life Incident:** Thuringia Incident (2022) – On June 22, 2022, a train collided with a Euro pallet that had been left on the tracks.[12]
   - **Scenario Details:** This scenario simulates the detection of medium-sized debris on the tracks, requiring an automated response to prevent potential derailment or damage.

8. **NRS: Animal on Track**
   - **Description:** An animal, such as a deer, a boar or a sheep, standing or moving across the tracks.
   - **Real-Life Incident:** Train Derailment near Fulda (2008): ICE Train derailed after hitting a herd of sheep in a tunnel.[13]

Scenario Details: This scenario simulates the detection of animals on the tracks, a common occurrence in rural areas. The ability to detect and respond to such obstacles is vital to prevent significant accidents. **Remark by SNCF:** It is important to note that when considering the entire French territory, including the greater Paris region in the distant suburbs, which are mostly covered by hedgerows or large forested areas, collisions with wild animals are reported daily: wild boars, does, deer, all types of game, as well as smaller animals such as foxes and large rodents are regularly struck by regional trains, with TGVs generally benefiting from anti-intrusion systems. Among the animals encountered along the train's route, the possibility of including an exotic animal in the list was discussed. Beyond the fact that an animal such as a giraffe could escape from a zoo and wander near a railway track, we pursued ambitions of explainability and robustness: we must ultimately be able to prove that any element encountered, which could create a non-regular situation, must have the potential to be detected by an AI algorithm or any intelligent device. The simulation helps to represent such scenarios, no matter how improbable they may be in real life.

[11] (Hollenstein, 2024)

[12] (ots, 2022)

[13] (dpa/cl, 2008)

3.2.1.2 Category: Static Objects Hung on Infrastructure / Train

1. **NRS: Car Hanging from Bridge**
    - **Type:** Obstacle
    - **Description:** A car precariously positioned on a bridge, possibly after an accident.
    - **Real-Life Incident:** Oise, Breuil-le-Vert (2023): Car first hanging in security net of the bridge[14]
    - **Scenario Details:** This scenario tests the ability of the system to detect objects that are not directly on the tracks but are in close proximity, which could affect the safe passage of trains.
2. **NRS: Bag or Jacket on Train Door**
    - **Type:** Environment
    - **Description:** Bag in train door (2021): A bag or jacket caught in the door, hanging outside the train.[15]
    - **Real-Life Incident:** Bag caught in a train door, flapping in the wind.
    - **Scenario Details:** This scenario simulates the dynamic detection of moving objects that are attached to the train, reflecting real-world operational challenges that require accurate sensor detection.
3. **NRS: Unsecured Load on Freight Train**
    - **Type:** Environment
    - **Description:** A load, such as a metallic beam, that has shifted and is protruding from a wagon.
    - **Real-Life Incident:** Hypothetical Scenario – This represents a potential danger from unsecured freight.
    - **Scenario Details:** This scenario tests the sensors’ ability to detect and respond to dynamic, dangerous protrusions from moving trains, which could pose significant safety hazards.
    -
4. **NRS: Covering Foil on Loads**
    - **Type:** Environment
    - **Description:** A large cloth or tarpaulin covering a load, flapping in the wind.
    - **Real-Life Incident:** Freight Train Scenario – Common in freight operations.
    - **Scenario Details:** This scenario evaluates the system's ability to track and respond to dynamic objects that change shape and position, which is crucial in maintaining safety during freight transport.
5. **NRS: Malicious Acts**
    - **Description:** Malicious acts aimed at damaging infrastructure, such as catenaries, before or during the passage of a train

[14] (Rifflet, 23)

[15] (Lynn Sachs, 2021)

- **Real-Life Incident:** Montagny-Sainte-Félicité (2008): Iron rods attached to catenaries[16]
- **Scenario Details:** This scenario simulates detection and response to malicious activities that could harm rail operations, emphasizing the importance of preventive measures to ensure safety.

3.2.2 3D Models of Static NRS Obstacles

In collaboration of Deutsche Bahn and SNCF, various 3D models of static NRS obstacles were developed and integrated into the simulation environment. These obstacles included items such as large rocks, pallets, and supermarket trolleys. Each model was carefully designed to reflect the physical characteristics of real-world objects that have been encountered on railway tracks. The models were textured and configured to behave realistically within the simulation, allowing the sensors on the trains to interact with them in a manner similar to real-life scenarios.

The static NRS obstacles were selected based on their relevance to both French and German railway environments, ensuring that the simulations cover a wide range of possible incidents. For example, scenarios involving objects on the track were compared to historical incidents like the Bad Driburg Derailment (2024) and similar events in France, providing a robust framework for testing the effectiveness of the simulation models.

The 3D modelling of Non-Regular Situation (NRS) obstacles is a crucial component of the simulation scenarios in Deliverable D7.3. These models are designed to reflect real-world obstacles that trains might encounter on the tracks, allowing for realistic and effective simulations.

Figure 7 NRS Van on tracks

An example of this is depicted in the figure, where a van is positioned on the railway tracks within the simulation environment. This scenario is designed to replicate a situation where a vehicle is inadvertently left on the tracks, a scenario that has occurred in various real-world incidents.

[16] (leparisien.fr, 2008)

- **Key Features of the 3D Model:**
  - **Realism**: The van model includes detailed textures and accurate physical dimensions, ensuring it behaves realistically when interacting with the train and its environment within the simulation.
  - **Positioning**: The van is placed directly on the tracks, simulating a scenario where a vehicle has either stalled or been mistakenly left in a dangerous position, posing a significant hazard to oncoming trains.
  - **Simulation Objectives**: The primary objective of simulating such a scenario is to test the sensors' ability to detect large static obstacles on the tracks in time to initiate emergency braking or other automated responses.
- **Relevance to Real-Life Incidents:**
  - This scenario can be compared to real-world incidents such as the **Berlin Incident (2022)**, where a passenger train collided with a construction vehicle on the tracks. By accurately modeling such situations, the simulation helps in developing robust automated systems capable of preventing similar accidents.

This example demonstrates the level of detail and realism that is being integrated into the simulation scenarios, ensuring that the outcomes provide valuable insights into the effectiveness of the sensor and AI systems being developed.

Figure 8 NRS wooden pallets on the tracks

Continuing with the examples of static Non-Regular Situation (NRS) obstacles, another scenario depicted in the simulation environment involves a stack of wooden pallets placed on the railway tracks. This scenario is particularly relevant for testing the detection capabilities of train sensors when faced with smaller, yet potentially hazardous, obstacles that could cause significant damage or derailment.

Key Features of the 3D Model:

- **Realism**: The wooden pallets are modelled with high detail, including their structure and texture, to accurately represent the potential danger they pose if left on the tracks.
- **Scenario Setup**: The pallets are arranged in a manner that simulates a real-world scenario where debris or construction materials might accidentally end up on the tracks, especially in industrial or urban areas.
- **Simulation Objectives**: The aim is to test the sensors' ability to detect relatively small, yet complex, obstacles that could be easily overlooked but still pose a serious threat to train safety.

Relevance to Real-Life Incidents:

- This scenario is designed to simulate incidents similar to **construction or maintenance-related debris** left on tracks, which has been a cause of accidents in the past. By modelling such scenarios, the simulation provides a realistic testbed for developing and fine-tuning sensor algorithms that need to detect a wide variety of obstacles, ensuring comprehensive safety measures are in place.

These detailed 3D models and their integration into the simulation environment allow for thorough testing and validation of the sensors and automated systems that will be crucial for the future of railway safety and automation.

4 SIMULATION SCENARIOS

4.1 DEFINITION OF SIMULATION LOCATIONS

For Deliverable D7.3, the simulation scenarios are set exclusively on a specific section of the Hamburg S-Bahn track, covering the route from Rothenburgsort to Bergedorf. This segment of the railway network was selected due to its complexity and the diverse range of operational conditions it offers, making it an ideal environment for testing and validating the sensor and automated systems developed within the R2DATO project.

Location: **Hamburg S-Bahn Track 21 (Rothenburgsort to Bergedorf)**

Description: This route includes a variety of urban infrastructure elements such as stations, rail crossings, bridges, and tunnels. The section is characterized by high traffic density, frequent interactions with urban elements, and a mix of straight tracks and curves. It presents a challenging environment that is representative of the conditions under which the sensors and automated systems must operate reliably.

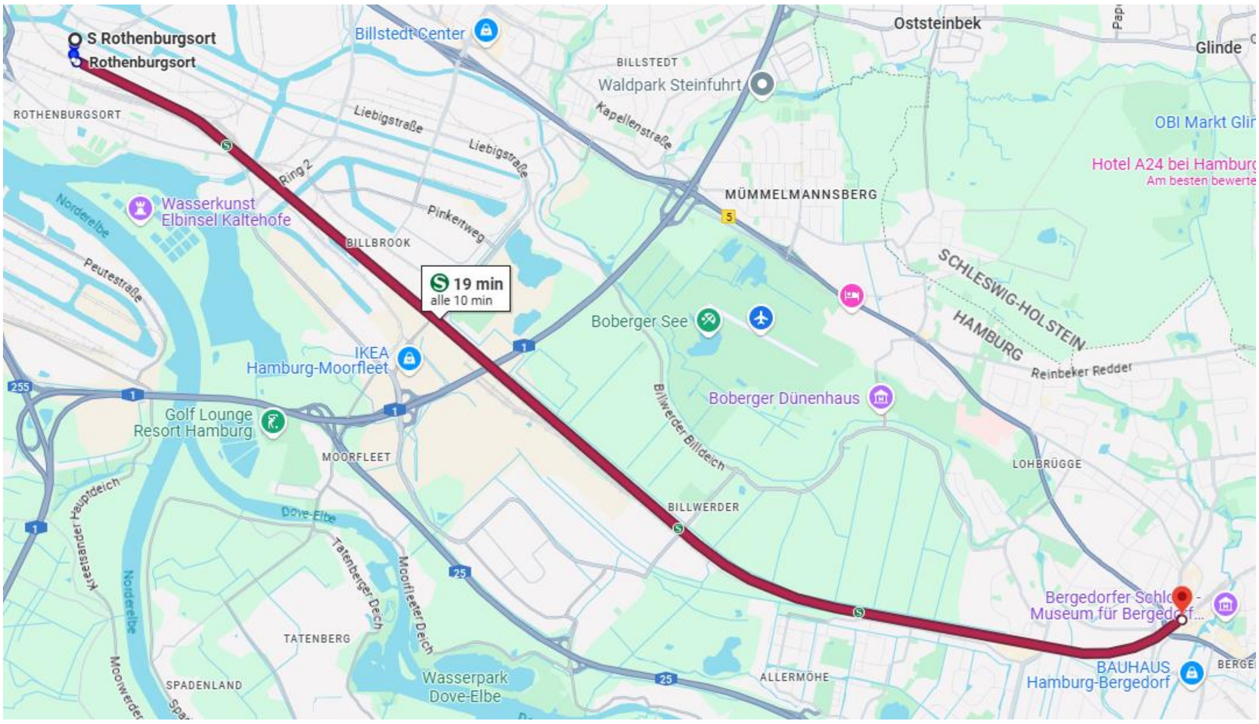


Figure 9 Hamburg S-Bahn Track 21 (Rothenburgsort to Bergedorf) Image © 2024 Google.

Use of French Models: In this simulation, detailed 3D models of French trains and infrastructure are integrated into the Hamburg S-Bahn environment. This approach allows for the testing of sensor systems in a realistic setting while using models that reflect the design and operational characteristics of French railway vehicles and infrastructure.

4.2 Description of Regular and Non-Regular Scenarios

In Deliverable D7.3, the simulation focuses on both regular operational scenarios and Non-Regular Situations (NRS) to thoroughly test the system's capabilities. However, due to current limitations in the simulation environment, only static objects are being simulated at this stage.

1. **Regular Scenarios**:
   - **Routine Operations**: These scenarios involve typical train operations such as station stops, accelerations, decelerations, and normal signal adherence along the Rothenburgsort to Bergedorf route. These scenarios ensure that the system performs reliably under standard operational conditions without unexpected events.
   - **Standard Obstacle Detection**: The system is tested for its ability to detect and react to common obstacles on the tracks, such as small debris, under regular operational conditions.
2. **Non-Regular Situation (NRS)**:
   - **Static Objects on Track**: For the moment, the simulations are focused exclusively on static objects, such as supermarket trolleys or construction materials (e.g., pallets) that are left on the tracks. These objects are placed at various points along the simulation route to replicate real-life scenarios where such items might be accidentally left on the tracks.
     - **Reason for Focusing on Static Objects**: Based on discussions, it was decided to focus on static objects due to the challenges posed by the current simulation setup, particularly the heavy data load and the need to ensure smooth performance without significant lag. The decision to prioritize static objects allows for detailed testing of the system's capabilities under controlled conditions, without overloading the simulation platform.
   - **Dynamic Objects**: Although not currently simulated, dynamic objects such as a jacket flapping from a train door or stray animals crossing the tracks are planned for future simulations. These scenarios will be critical for testing the sensors' ability to detect and react to moving objects, which is essential for ensuring passenger and operational safety.
   - **Infrastructure Failures**: Similarly, scenarios involving infrastructure failures, such as signal malfunctions or track anomalies, are acknowledged but are not part of the current simulation phase. These scenarios will require more advanced simulation capabilities and are intended to be included in later stages of the project.

By focusing on static objects at this stage, the project ensures that the simulation environment remains manageable and performs reliably, allowing for a thorough analysis of the system's capabilities under these conditions. Dynamic objects and infrastructure failures will be incorporated into the simulation as the platform's capacity and performance are further optimized.

4.3 Scenario Selection Process

The scenarios selected for the simulation were carefully chosen to maximize the relevance and challenge of the tests. The selection process involved close collaboration between SNCF, Deutsche Bahn, and the technical teams within the R2DATO project.

1. **Focus on Realism**:
    - Given the exclusive use of the Hamburg S-Bahn route, scenarios were designed to reflect the real operational challenges encountered on this specific track. Historical incident data from similar urban rail environments was reviewed to identify common obstacles and situations that could be realistically modeled.
2. **Integration of French Models**:
    - The decision to use French train models on the Hamburg track was driven by the need to validate the sensor systems across different vehicle designs and configurations, ensuring robustness and adaptability.
3. **Safety-Critical Testing**:
    - Scenarios were selected with a strong emphasis on safety, particularly in testing the sensors' and systems' ability to prevent accidents in high-risk situations. This includes the detection of both static and dynamic obstacles, as well as responses to unexpected infrastructure failures.
4. **Challenging Conditions**:
    - The chosen scenarios were specifically designed to push the boundaries of the sensor systems' capabilities, ensuring that they can handle complex and potentially hazardous conditions that are representative of urban railway environments.

By focusing on a specific, challenging section of the Hamburg S-Bahn and integrating models that reflect French rail characteristics, the simulation scenarios provide a robust framework for testing the effectiveness of the R2DATO project's technological developments.

5 SENSOR DATA AND SIMULATION

5.1 SENSOR TYPES AND DATA USAGE

In the simulation environment for Deliverable D7.3, two types of sensors are integrated to capture critical data that informs the development and testing of automated systems in railway operations. The key sensors utilized include:

1. **LiDAR (Light Detection and Ranging)**:
   - The RTX LiDAR is preconfigured with the Ibeo Next.
   - **Purpose**: LiDAR sensors generate detailed 3D maps by measuring distances to objects around the train. This data is essential for accurately detecting and classifying obstacles both on and near the tracks.
   - **Data Usage**: The LiDAR data is converted into point clouds, representing the environment, which helps the system identify and track both static and dynamic objects in the simulated scenarios. More than just 3D point clouds, the system also provides data on the speed and reflectivity of objects, enhancing the detection and analysis capabilities.
2. **Cameras**:
   - The sensor cameras were configured using Sony's IMX490 sensor, with parameters set according to its open technical specifications. Additionally, the cameras were equipped with virtual Fujifilm HF50SA-1 lenses.
   - **Purpose**: High-definition HDR cameras, mounted at the front of the train, capture visual data of the track ahead. This visual information is crucial for real-time object detection and classification within the simulation.
   - **Data Usage**: The camera feeds are processed to identify and classify obstacles such as vehicles, debris, and other hazards, providing contextual visual information that complements the data from other sensors.
   - **Resolution Considerations**: Initially, three cameras were used with high-resolution settings (2896x1876), resulting in a significant data load (approximately 15 MB per image at 30 FPS). Due to the heavy data load causing simulation lag, it was decided to maintain a standard resolution of 1544x1032 for most ROS Bags files, with the option to apply higher resolution in post-processing if necessary.

5.2 Sensor Placement and Configuration

The sensors in the simulation environment are strategically placed to ensure that the data collected is comprehensive and accurate:

1. **LiDAR Placement**:
   - **Positioning**: LiDAR sensors are mounted on the top front of the train, offering a wide field of view with the ability to detect objects both around the train and directly ahead. This positioning allows for comprehensive situational awareness with focused detection in the train's forward path.
   - **Configuration**: The sensors' fields of view are configured to overlap slightly, ensuring continuous environmental monitoring, particularly in areas with complex track geometry.
2. **Camera Placement**:
   - **Positioning**: Cameras are mounted at the front of the train, providing a clear view of the track ahead.
   - **Configuration**: The cameras are configured to capture wide-angle views, ensuring that the tracks and adjacent areas are thoroughly monitored within the simulated environment. Adjustments were made to the cameras based on received technical specifications, ensuring proper alignment and functionality within the simulation.

5.3 Sensor Data Synchronization and Processing

In the simulation, data processing is crucial for achieving realistic and actionable results. The following steps outline how sensor data is handled within the simulation environment:

1. **Data Collection and Simulation**:
   - **Initiation and Data Capture**: The simulation begins with the generation of sensor data, replicating what would be collected onboard a real train. Data from LiDAR, cameras, radar, and ultrasonic sensors are simulated to reflect real-world conditions.
   - **Simulation Platform Processing**: Unlike real-world data, which would be transferred to a Data Center, all data processing occurs within the simulation platform. This platform simulates the functions of a Data Center by handling data synchronization, processing, and storage virtually.
2. **Data Synchronization and Integration**:
   - **Virtual Synchronization**: The simulation platform synchronizes the data in real-time, aligning data streams from different sensors using virtual timestamping. This ensures that all sensor inputs are accurately correlated, providing a cohesive view of the simulated environment.
   - **Sensor Fusion in Simulation**: The platform employs simulated sensor fusion algorithms to combine data from various sensors, creating a detailed and accurate model of the environment within the simulation.
3. **Data Processing and Analysis**:
   - **Simulated Processing**: Data is processed within the simulation platform, where virtual machines replicate the processing tasks of a real Data Center. This includes filtering, object recognition, and scenario analysis, performed in real-time within the simulated environment.
   - **Data Storage and Retrieval**: Processed data is stored within the simulation platform, allowing for post-simulation analysis and review. This data is crucial for evaluating sensor performance and refining algorithms in the simulated context.
4. **Rendering and Data Collection Challenges**:
   - **Current Setup**: The simulation setup includes tools like Teams, Omniverse, and virtual machines. High data load from the cameras has been identified as a challenge, causing lag during simulation.
   - **Proposed Solution**: To mitigate this issue, the resolution of ROSBAG files was lowered during data collection, with higher resolution reserved for final rendering purposes if needed for demonstration.
5. **Machine Learning and Model Testing**:
   - **Virtual ML Integration**: In the simulation, data is used to train machine learning models within the platform. These models are tested against various simulated scenarios to evaluate their effectiveness and robustness.
   - **Output in Simulation**: The final output of the simulation process is a set of trained models and detailed analysis of their performance, providing insights into how the system would function in a real-world setting.

These enhancements and adjustments ensure that the simulation environment provides a detailed and realistic testbed for evaluating the automated systems under development in the R2DATO project.

5.4 Simulation Flow

The simulation process for Deliverable D7.3 is designed to replicate real-world railway scenarios using a combination of real footage, 3D modelling, and advanced sensor simulation. Below is a detailed explanation of the simulation flow:

1. Scene Selection and Preparation

- **Real-World Footage Identification**:
    - The process begins by selecting a segment of real-world footage, specifically from recordings taken in locations such as Hamburg. The chosen footage serves as a basis for the simulated environment.
    - **Example**: A specific track segment from Hamburg was identified and chosen as the basis for simulation. This footage is carefully analysed to ensure that it captures relevant elements for the simulation, such as track layout, environmental conditions, and lighting.

Figure 10 Real Sensor Footage in Hamburg at Tidekanal's Bridge

- **Recreating the Scene in Simulation**:
    - Once the footage is selected, the scene is recreated within the simulation environment. This involves accurately modelling the railway track, surrounding environment, and key visual elements from the footage.
    - **Integration of Real Data:** Our simulation incorporates real-world data, such as GPS coordinates to map rail track system and environmental conditions, to ensure that the virtual scene closely mirrors the actual location. In this case, the real footage was recorded in Hamburg during winter around 15:00 hours. To closely replicate these conditions within the simulation, we configured the following settings in the simulation:

Time of Day:	15
Day of the Year:	60
Latitude (GCS):	53.5511
Longitude (GCS):	9.9937

Table 2 Environment Settings Simulation

By using these precise settings, we can simulate the sun's position and daylight conditions as they would appear in Hamburg at that specific time and date. This integration of real-world data ensures that our virtual environment closely aligns with the real-world scenario, providing consistency and accuracy in our simulation results.

Figure 11 Hamburg Scene at Tidekanal's Bridge

2. 3D Modeling and Obstacle Placement

- **3D Asset Integration**: Partners provide a set of 3D models representing various obstacles that could be encountered on the tracks. These include static objects like a van, a trolley, pallets, and rocks.

Figure 12 3D Assets implemented in the simulation: Rock, Pallets, Trolley, and Van

  - **Example**: A van model is integrated into the simulation to replicate a potential obstruction on the tracks.

Figure 13 3D Hamburg Scene at Tidekanal’s Bridge With Van as an Obstacle.

- **Placement of Obstacles**:
  - The 3D models are strategically placed within the simulated environment to create realistic scenarios. For this phase, only static objects are included due to current simulation limitations.
  - **Static Focus**: The simulation currently focuses exclusively on static objects, such as construction materials left on the tracks. This decision was made to ensure the simulation runs smoothly without overloading the system.

3. Sensor Configuration and Simulation Setup

- **Sensor Setup on the Train Model**:

- The simulated train is equipped with multiple simulated sensors, including cameras and LiDAR. The configuration is designed to mimic real-world sensor setups as closely as possible.
- **Camera Sensor Configuration**:
  - **Three Camera Sensors:** The train model is equipped with a set of three cameras, all of which are designed to capture high-resolution visual data of the track and surrounding environment. Each camera is a **Sony IMX490**[17], equipped with a **Fujinon HF50SA-1**[18] lens. This camera model is renowned for its exceptional image quality, wide dynamic range, and low-light performance, making it ideal for accurately capturing visual details of the track under various lighting conditions.
  - The cameras are strategically placed to optimize coverage: a central camera is mounted on top of the train to provide a direct view ahead, while the other two cameras are positioned on the left and right sides to create stereo vision setups. This configuration allows the system to model spatial relationships accurately and detect obstacles with high precision, leveraging detailed depth perception of the environment.
  - **Resolution Challenges**: In the simulation, we intentionally reduced the resolution, frame rate, and color depth compared to the real sensors to optimize the performance of the simulation.

    While we can adjust most of the simulation parameters to match the real sensor specifications, doing so would introduce significant latency between frames, hindering the efficiency and responsiveness of the simulation. For this initial use case, we prioritized a lower quality setting to ensure smoother and faster simulation performance. This allows us to run the simulation more efficiently, with less computational load and quicker processing times. After collecting the raw data from the simulation, we can apply post-processing techniques, such as interpolation methods (like bilinear or bicubic interpolation) and deep learning-based super-resolution models such as ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) or SRCNN (Super-Resolution Convolutional Nueral Network) , to enhance the quality of the data as needed.
- **LiDar Configuration**:
  - **Simulation of Sensor Data**:The simulation environment generates data as if it were being collected in a real-world scenario. The sensors capture information about the obstacles placed in the environment, including visual data from the cameras and 3D point clouds from the LiDAR.

[17] (sony-semicon.com, 2024)

[18] By using the lens the resolution is reduced because the light doesnt reach all oft he sensors surface

- **Rendering and Textures:** Initially, there were issues with missing textures on the 3D models. These were corrected, and the updated renderings were successfully incorporated into the simulation.

4. Data Collection and Processing

- **Data Recording**:
  - The simulation records data in ROS bag format, capturing all relevant sensor outputs, including camera feeds and point clouds from LiDAR.
  - **Data Volume**: The simulations generate large data files (e.g., 24 GB for a 30-second recording). This reflects the high resolution and detailed data points collected by the simulated sensors.
- **Post-Simulation Processing**:
  - Once the data is recorded, it is stored and processed within the simulation platform. The recorded data is used to analyse the performance of the sensors and to refine the simulation parameters.
    - **Bounding Boxes**: Bounding boxes are generated in the simulation to highlight detected objects. These are computed by the software, not directly from the camera feeds, to provide a visual indication of the objects' positions relative to the sensors.

5. Rendering and Finalization

- **Final Rendering**:
  - After data collection, the simulation produces final renderings of the scenarios. These renderings are designed to be visually detailed and are used for both analysis and presentation purposes.
    - **Marketing and Presentation**: The high-quality renderings are also used for marketing and demonstration purposes, helping stakeholders understand the simulation results.
- **Documentation and Sharing**:
  - The simulation process and results are documented thoroughly. Details such as camera configurations, sensor specifications, and rendering settings are recorded in Confluence and other documentation platforms.
    - **Feedback and Corrections**: Any issues encountered during the simulation, such as incorrect texture exports, are corrected and updated renderings are shared with the team.

This detailed simulation flow outlines the entire process from scene selection to final rendering and documentation, ensuring that every step is planned and executed to create realistic and actionable simulation data for the R2DATO project.

6 SIMULATION EXECUTION

6.1 PREPARATION AND SET-UP

The simulation setup employs **NVIDIA Isaac Sim 2022.1**[19], an advanced platform ideal for constructing and managing intricate virtual environments. Isaac Sim is particularly suited for this project due to its extensive support for virtual sensors, such as cameras and LiDARs, which are essential for accurate simulations.

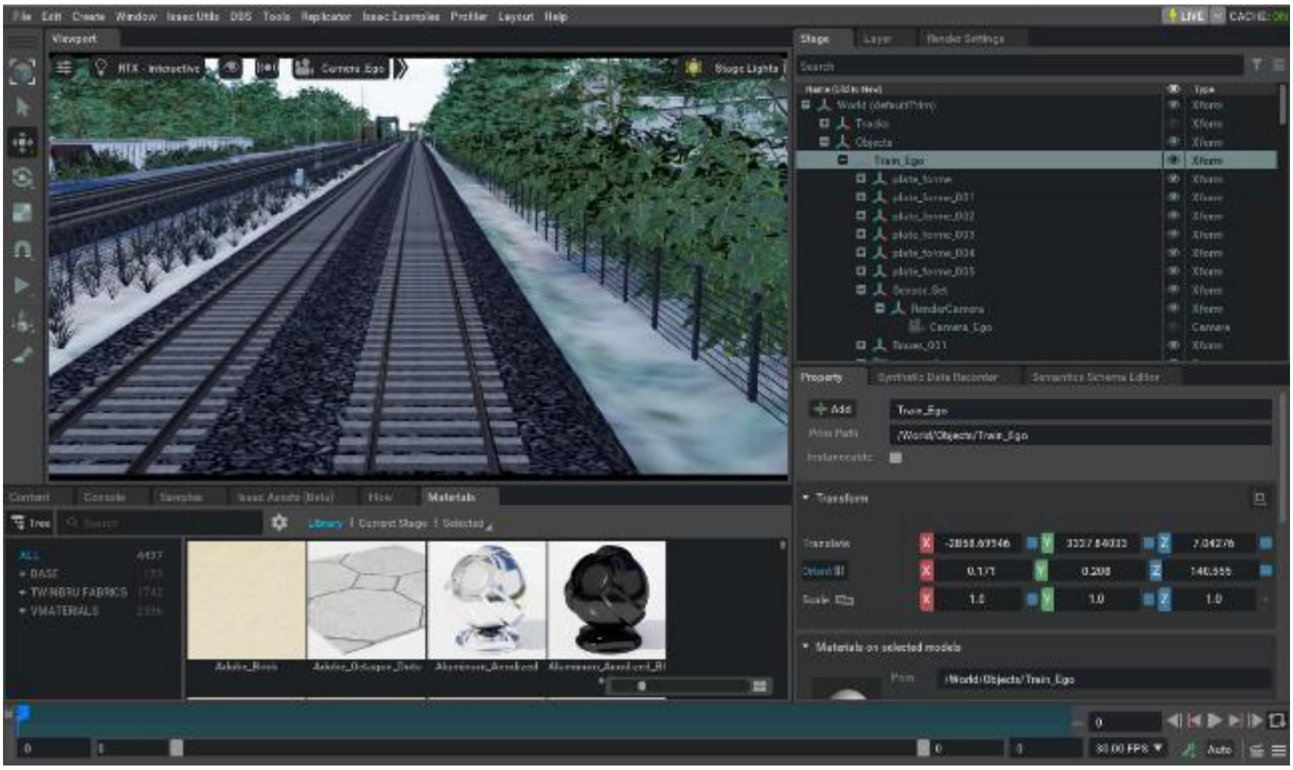


Figure 14 Simulation Environment Setup Using NVIDIA Isaac Sim 2022.1 for Virtual Sensor Integration and High-Fidelity Simulations

Key advantages of Isaac Sim include:

- **Virtual Sensor Integration:** Isaac Sim enables precise configuration, placement, and management of various virtual sensors, crucial for replicating real-world sensor behavior and conditions. This ensures the data generated is both realistic and reliable.
- **High-Fidelity Simulations:** The platform excels in producing simulations that closely mirror real-world environments, providing the necessary detail for thorough analysis and achieving project objectives.
- **Flexibility and Efficiency:** Isaac Sim's intuitive interface and adaptable tools allow for the efficient setup of complex simulations, reducing setup time and enabling rapid iterations. This efficiency is critical for meeting project deadlines and delivering high-quality outcomes.

Overall, **NVIDIA Isaac Sim 2022.1** delivers the robust capabilities required for sophisticated simulations, making it an indispensable asset in meeting the project's rigorous standards.

[19] (developer.nvidia.com, 2024)

6.2 Simulation Runs

The simulations were run on an OVX virtual machine with full access to an NVIDIA A100 graphics card on the OVX server. NVIDIA OVX systems are optimized for high-fidelity digital twins and complex simulations, providing powerful GPU resources for real-time rendering, physics simulation, and AI acceleration, ensuring detailed and accurate virtual environments.

For our simulation runs, we selected four Non-Regular Situations (NRS) featuring obstacles such as a van, a trolley, a rock, and pallets on the track.

- Each simulation is designed to closely replicate these specific scenarios.
- The length of each simulation run is 30 seconds (Simulation time), matching both the duration of the final rendered videos and the ROS bag recordings.
- This duration also aligns with the real footage, allowing us to showcase significant infrastructure such as bridges, train stations, rail infrastructure, and vegetation, providing a realistic view of the environment.

6.3 Data Recording and Video Rendering

6.3.1 Data Recording

The sensors are configured to publish ROS messages by topics in real-time during the simulation. To effectively record this data, we utilize our custom-built software, which subscribes to the available topics and records the ROS messages in parallel as they are broadcasted. This software is designed specifically to record the incoming messages into ROS bags for future analysis.

These ROS bags are saved using ROS2 Humble, with the data stored in the .mcap file format, which is the standard for efficiently recording and managing large volumes of ROS data. This setup ensures a streamlined process for both simulation and data capture, making the collected data readily available for any necessary post-processing or analysis.

During each simulation run, ROS bags are recorded, storing data from four primary topics. Each of these topics is associated with specific sensors that provide detailed information from each simulation row:

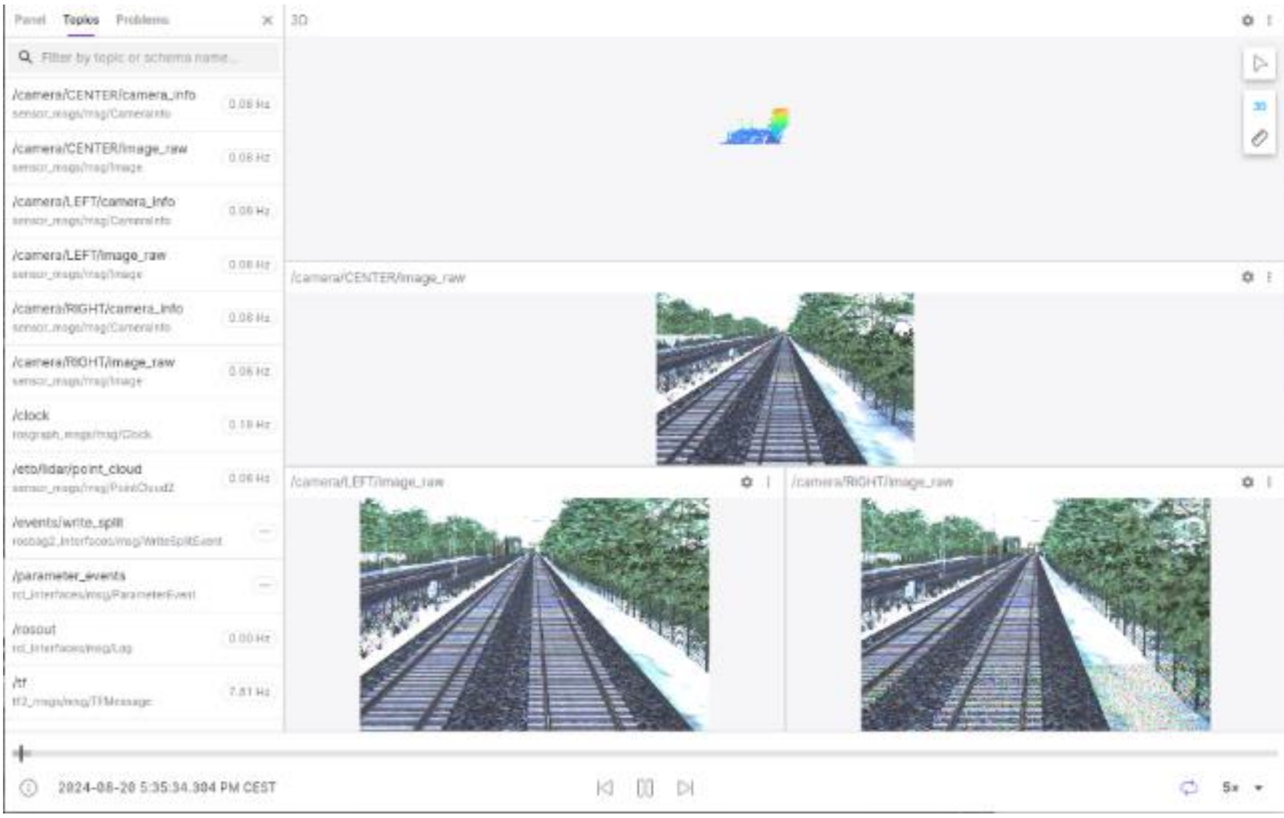


Figure 15 Visualisation of the ROS Bag File in Foxglove

Topics:

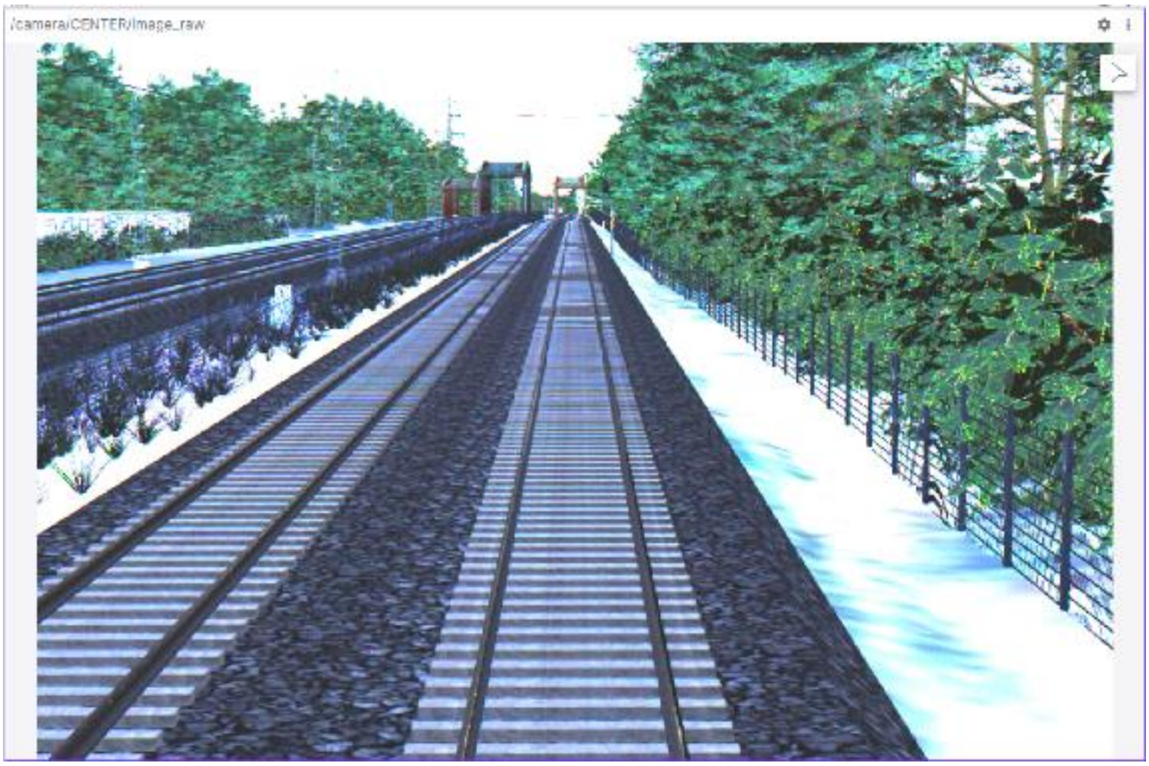
1. **/camera/CENTER/image_raw**:
   - **Sensor**: IMX490
   - **Data Type**: Image data
   - **Description**: This topic streams raw image data from the IMX490 sensor, which is centrally positioned. The data consists of unprocessed image frames, serving as the primary visual input for tasks such as object detection, tracking, or general scene analysis.
   - 

     Figure 16 Visualisation of output from center camera

2. **/camera/LEFT/image_raw** and **/camera/RIGHT/image_raw**:
   - **Sensors**: IMX490 (both LEFT and RIGHT as stereo system)
   - **Data Type**: Stereo image data
   - **Description**: These topics stream synchronized raw image data from the HF50SA-1 sensors positioned on the left and right sides, respectively. Together, they form a stereo camera system, providing two perspectives of the same scene. This setup enables depth perception and 3D reconstruction by capturing the slight differences between the left and right images, which can be used for tasks such as depth estimation, obstacle detection, and 3D mapping.

Figure 17 Visualisation of output from left camera

Figure 18 Visualisation of output from right camera

3. **/etb/lidar/pointcloud**:
   - **Sensor**: Ibeo Next 11

- **Data Type**: Point cloud data
- **Description**: This topic streams point cloud data generated by the Ibeo Next 11 LIDAR sensor. The data provides 3D spatial information about the environment, crucial for tasks such as environment mapping, object detection, and navigation.

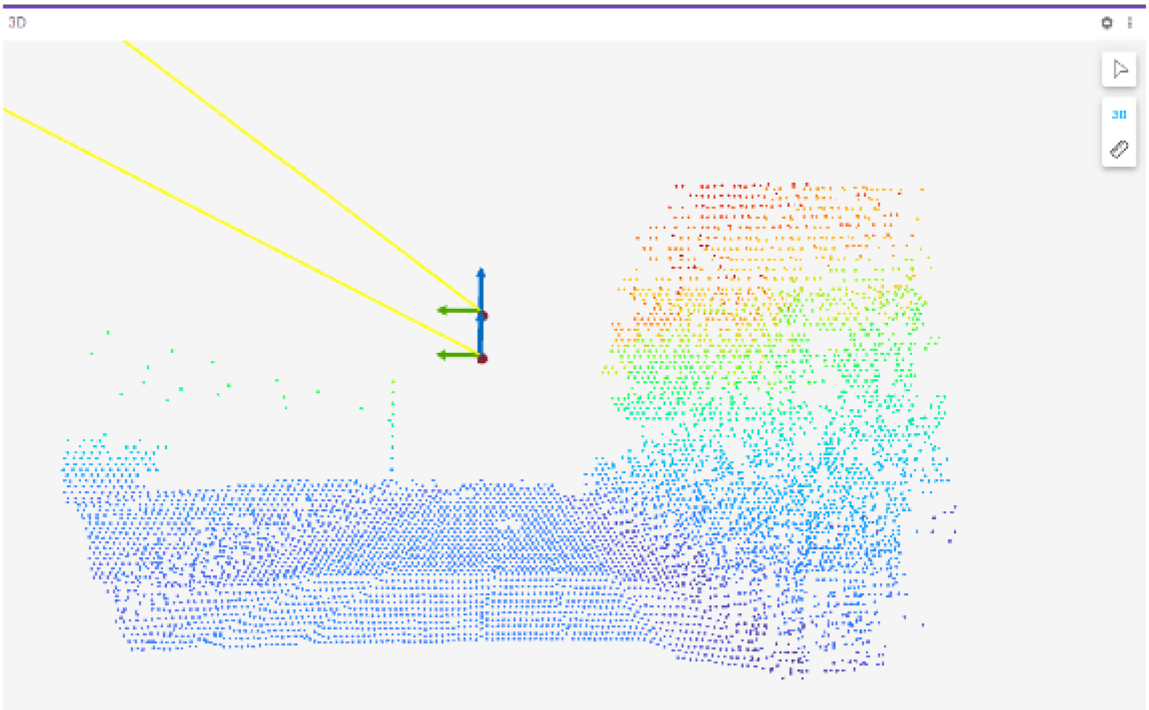


Figure 19 Visualisation of point cloud from LiDAR

6.3.2 Video Rendering

The final videos were rendered in high resolution at **2896 × 1876** pixels to ensure detailed and clear visuals. Each video has a duration of 30 seconds, corresponding exactly to the length of the ROS bag recordings.

The camera used for these renders was mounted on the top center of the train's front, providing an optimal view of the track and obstacles.

To support different analysis needs, we produced two versions of each render:

- **With Bounding Boxes:** The bounding boxes are highlighted using Omniverse Isaac Sim and not through any algorithmic detection. This allows us to visually identify and track the objects in the scene without relying on external detection algorithms.

Figure 20 Static Object Stone with bounding box

Figure 21 Static Object Trolley with bounding box

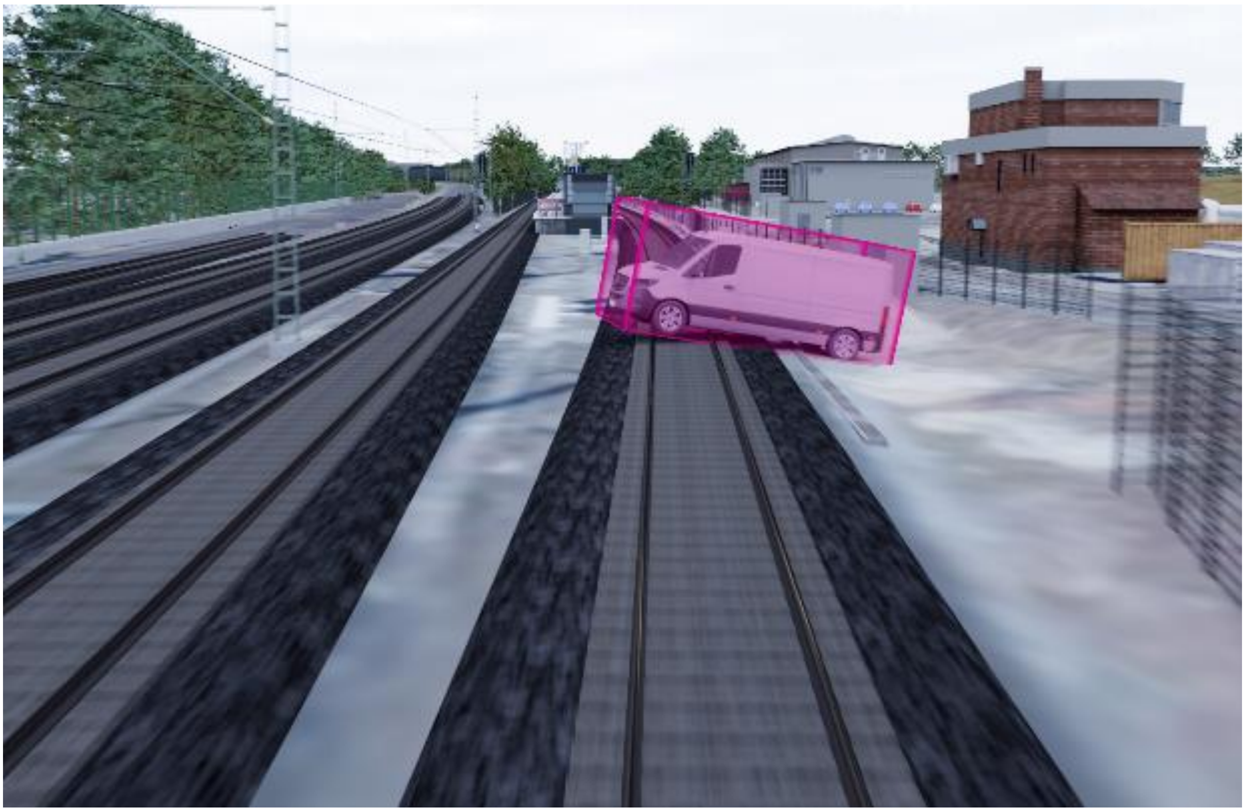


Figure 22 Static Object Van with bounding box

Figure 23 Static Object Pallets with bounding box

- **Without Bounding Boxes:** This version presents the scene as it naturally appears, without any visual annotations. These two versions enable thorough evaluation and comparison, accommodating both automated processing and manual review, while clarifying that the bounding box annotations are purely a feature of the simulation environment.

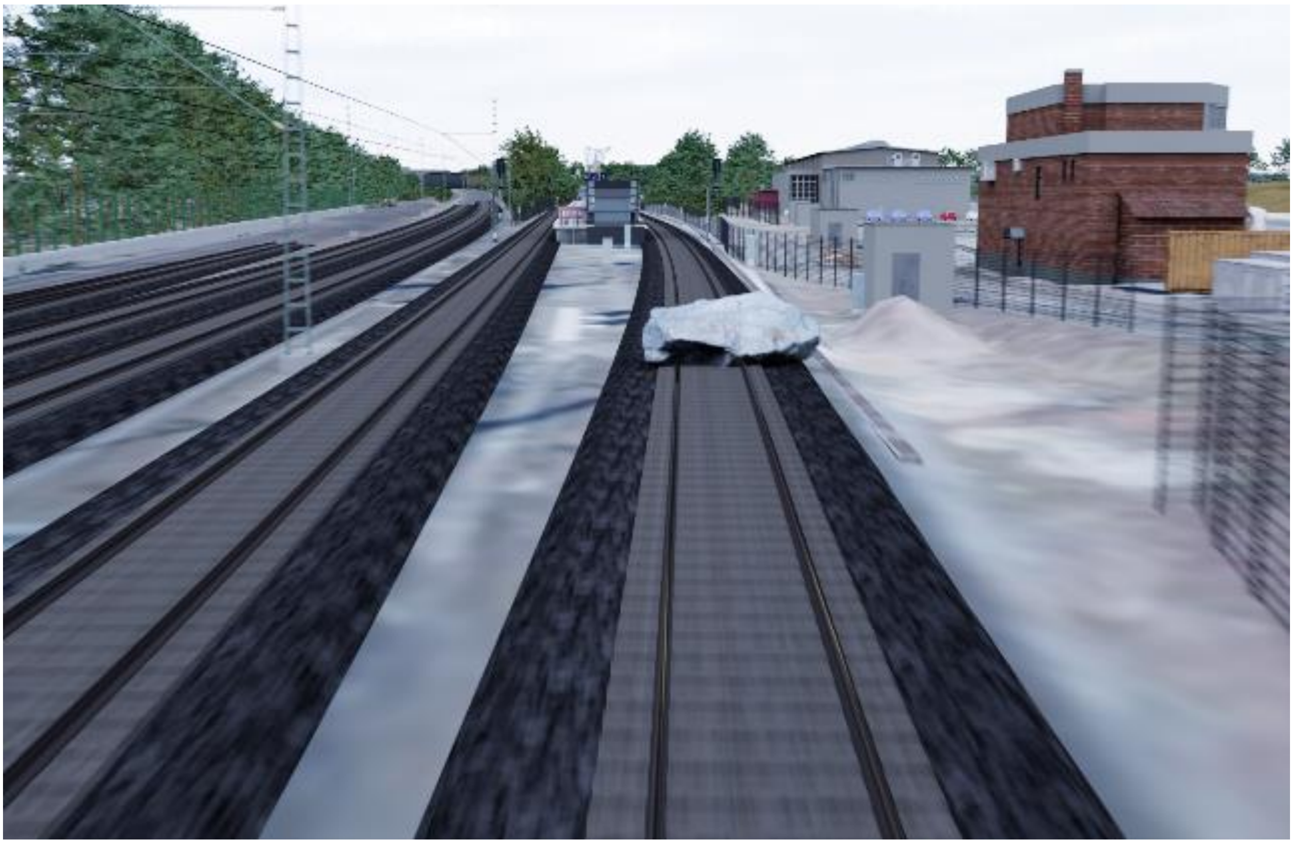


Figure 24 Static Object Stone without bounding box

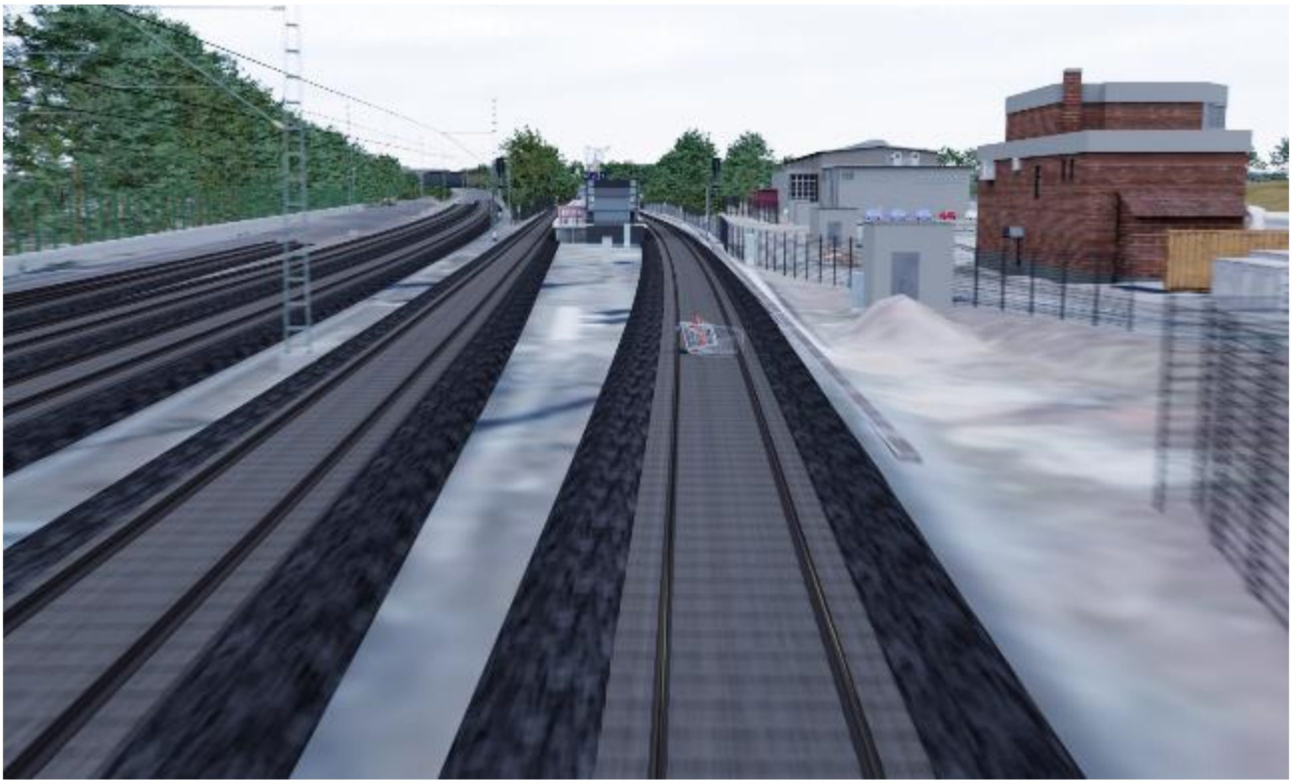


Figure 25 Static Object Trolley without bounding box

Figure 26 Static Object Van without bounding box

Figure 27 Static Object Trolley without bounding box

7 PROSPECTIVE VIEW ON ENHANCING SIMULATION IMAGERY WITH NEURAL NETWORKS

This chapter, focusing on enhancing simulation imagery through neural networks, was developed exclusively by SNCF. It does not represent collaborative work. SNCF conducted independent research to identify algorithms and AI methods that could be leveraged to create visual environments conducive to the validation of pre-trained algorithms and potentially for future training or refactoring purposes.

7.1 IS SIMULATION AN ASSET?

7.1.1 Context

On the SNCF side, research was conducted to identify algorithms and AI methods that could be leveraged to create visual environments conducive to the validation of pre-trained algorithms, or even, in the more distant future, for training or refactoring purposes. Solutions were benchmarked and studied in a state-of-the-art review. Subsequently, a series of developments allowed the use of images from simulations to which style transfer methods and transformations performed by generation engines based on generative AI were applied. The goal is to make these images as realistic as possible by making them resemble images captured by a camera. One of the first challenges encountered was computational power; therefore, the working samples were reduced to 3-second videos, and parallelization research had to be conducted, notably using the technique provided by DDP (Distributed Data Parallel). This technique of transformation and image generation helps consolidate simulated approaches and offers the possibility of enhancing datasets of images captured by a front-facing camera by adding various weather conditions, depending on the seasons (fog, mist, rain, snow), and at different times of the day (dawn, midday, and dusk), which is the aim. Scenario creation on a 3D simulator allows for the management of the non-regular situations described in this document by incorporating 3D assets as obstacles on the tracks or those about to become obstacles - situations that are never filmed and would be very costly to capture with a camera. Finally, the generated results need to be tested by applying pre-trained detection algorithms on these produced images to measure the difference in accuracy between a prediction made on a real image and the accuracy rate observed on a realistic image (synthetic image with both style transfer and transformation techniques) using the same algorithm.

This is a theoretical approach that requires testing on synthetic images, real images, and rendered real images to build a roadmap for validating these results in section 0.

7.1.2 Objectives

As part of the project, the use of artificial intelligence for image generation is a powerful tool for producing models that meet the needs of the railway industry. This project aims to produce realistic images from synthetic images created by 3D simulators. These realistic images are essential to improve the accuracy and robustness of computer vision models used for various applications, such as obstacle detection, irregular situations, infrastructure monitoring, or passenger security.

The main challenges that this project seeks to address are as follows:

Insufficient training data: Computer vision models require large amounts of data to be trained effectively. However, obtaining sufficient and varied datasets of images is often expensive and difficult, leading to incomplete results.

Model generalization: The models must be able to generalize well to unseen data during training. Without adequate data augmentation, models risk overfitting on limited datasets and may not perform well on real-world images under varied conditions. Moreover, explainability techniques (XAI) can today bring more information on the robustness of the generated models. Relying on new metrics such as the relevance of the pixels extracted through analysis methods of neural networks, could help to an objective data augmentation.
Diversity of scenarios: Application scenarios in the context of SNCF are diverse. It is crucial to simulate a wide range of conditions (weather, lighting, viewing angles, etc.) so that the models are robust and perform well in all situations.

One of the propositions would be to follow the hereafter workflow to lead exploitable datasets from combining both generative AI and 3D simulation techniques.

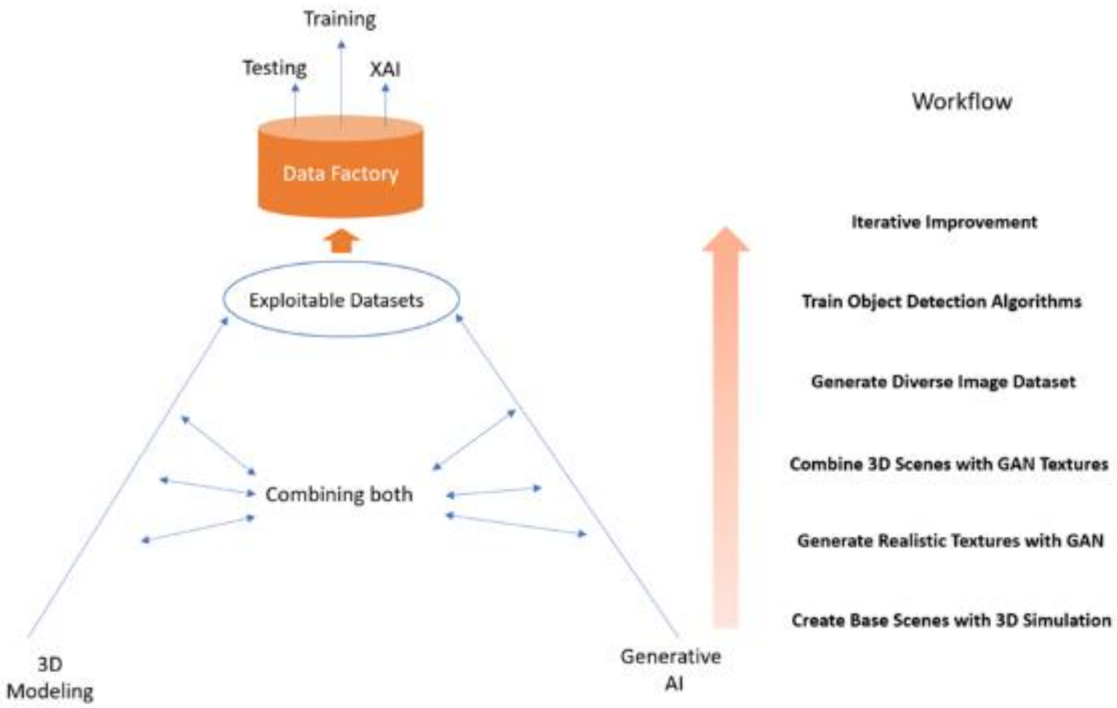


Figure 28 Workflow for dataset generation using 3D modelling and Generative AI

7.2 Towards a generative process

In general, SNCF aims to qualify future solutions developed by industry to detect events using AI. Simulation is one approach, but as mentioned earlier, it is not sufficient. In the future, a generation process capable of constructing consistent datasets will need to be proposed.

To better understand the work carried out as part of this project, it is important to remind the steps carried out as part of this project:

- First, preparing the datasets for each model and for each different weather condition. This was crucial as several image transformation models and several style transfer models were tested, showing varying results depending on the quality of the datasets.

- Then, high-performance generative AI models capable of generating high-quality images or producing many new images were applied. However, this required significant resources, despite the availability of two GPUs with 32 GB and 24 GB of memory, respectively.
- To overcome resource limitations, research was conducted to use the GPUs of other workgroup machines via Docker, instead of renting additional machines or outsourced computing capacity, which would have been too costly and exceeded the project's time frame.
- The application of different styles to images created with Unity3D was implemented. Although the resulting images were sometimes blurry, using models capable of transforming videos by changing their style as needed seemed more fruitful than transforming individual images.
- Thanks to these techniques, samples of short videos with different styles were produced, providing a wide variety of synthetic datasets.
- Finally, although this was not a primary objective of the project, the images were tested using the generated videos on an obstacle detection model. This allowed for a rough evaluation of the effectiveness of these obstacle detection models on the tracks. However, many more tests need to be conducted with open-source generalist algorithms and specialized algorithms developed internally. The goal is to measure the difference in detection accuracy applied to various sources, from natural images to fully synthetic images, and to analyze the differences produced to prove the relevance of the method.

Generation of Images

To start with, we explored various approaches to image generation based on real images. With the help of resources available on GitHub and research conducted by NVIDIA and Hugging Face, we were able to generate images. We primarily used models such as StyleGAN2 and DALL-E. However, the SNCF team encountered limitations in terms of the quality and quantity of generated images. The architecture of StyleGAN2, for example, allows for fine control over the styles of generated images but requires significant computational resources to produce high-quality images.

Style Transfer

Faced with the limitations of image generation, we turned to style transfer, a technique that allows modifying the appearance of an image by applying the style of another image; this can notably help in changing the context of the images, such as the environment, weather, etc. We explored several style transfer models, including the following:

- CycleGAN
- CUT (Contrastive Unpaired Translation)
- FATSCUT (FastCUT)
- UNIT (Unsupervised Image-to-Image Translation Networks)
- MUNIT (Multimodal Unsupervised Image-to-Image Translation)
- CycleGAN turbo
- U-GAT-IT

CycleGAN allows learning mappings between two domains without needing corresponding image pairs. CUT and FastCUT are optimized versions of CycleGAN, aimed at improving the speed and efficiency of style transfer. UNIT and MUNIT enable unsupervised image translation with advanced neural network architectures.

Technical building blocks :

- **Use of DDP and Docker**
- To overcome hardware limitations, we opted to use DDP (Distributed Data Parallel) in combination with Docker to leverage GPUs from different remote machines. The SNCF team successfully implemented this solution. This coordination of multiple skills led us to centralize databases and make them accessible via an API, rather than storing them individually on each machine.
- **DDP** (Distributed Data Parallel)
  Distributed Data Parallel (DDP) is a technique used to distribute deep learning model training tasks across multiple GPUs, thereby improving performance and reducing training time. According to sources, DDP in PyTorch has provided significant gains in training time using a data parallelization approach.
- **Docker**
  Docker is a containerization technology that allows for the development, shipping, and execution of applications within containers. Containers ensure that applications run consistently across different environments. Docker facilitates the "reproducible" aspect by providing a consistent and isolated environment for application execution.
- **MinIO**
  MinIO is a high-performance object storage system compatible with the Amazon S3 API. It is designed for a cloud-native infrastructure and is used for storing large amounts of unstructured data. The official documentation provides detailed information on the use and configuration of MinIO.

Advanced Video Transformation Models

Following the progress made, we decided to explore more advanced and larger models for video-to-video transformation based on textual descriptions. We specifically studied and used frameworks such as SliceIt, TokenFlow, and AnyV2V. These models rely on the use of the Stable Diffusion technique, and the results obtained have been very satisfactory from the perspective of artificial device perception. However, it is important to note that the level of realism perceived by the human eye is not the same as that captured by artificial systems. This distinction will be demonstrated throughout this thesis. The architecture of Stable Diffusion, for example, uses probabilistic diffusion models to generate high-quality images and videos from textual descriptions, combining techniques for transformation and image generation.

7.3 How to equip such a process

As part of this project, the contribution focused on using generative AI models to enhance the quality and diversity of images used in environmental simulations. To this end, the AI team engaged in the project equipped itself with a resource capable of producing at least a 3D simulation using Unity3D and Blender, to have control over time for creating irregular situations, without the complete set of a professional and sophisticated 3D scene as Deutsche Bahn is capable of. However, this is precisely the goal of such a European collaboration to bring together specialists from various fields. Without seeking to compete with German expertise, we felt the need to internalize this skill, at least for the testing period. The team was thus divided into two specialties: one for creating 3D videos, while the other focused on developing skills in applying style transfer techniques and stable diffusion to make these videos more realistic and controllable in their environment. This allowed us to generate synthetic datasets that can serve as targets for applying styles inspired by real photographs.

7.3.1 ERJU-WP7 Project: Towards an Advanced Data Factory

The ultimate goal of the ERJU-R2DATO WP7 project is to provide development communities with tools that enable the generation of datasets, launching of training, and validation of models. One of the methods that the Data Factory (DF) aims to produce is the large-scale transformation of 3D videos created with Unity3D using generative artificial intelligence techniques. This shared model is crucial for improving the learning and validation processes of deep learning algorithms by providing a continuous stream of enhanced and diverse data. The goal is to achieve a system where AI-generated data is indistinguishable from real counterparts, thus offering a perfect simulation for testing and training AI systems. This project directly contributes to the shared European vision of leveraging advanced technologies to optimize operations and ensure maximum safety across networks.

This interdisciplinary approach, combining 3D modeling and AI, places ERJU at the forefront of technological innovations in the railway sector, thereby enhancing operators' ability to anticipate and respond to future challenges.

7.3.2 Concrete Examples

Realistic Image Generation: Creation of realistic synthetic images from scenes generated by Unity3D.

Video Transformation: Application of advanced models to transform videos into videos with different styles, thus enhancing data diversity.

Resource Optimization: Implementation of DDP and Docker to efficiently use available GPUs and increase processing capacity.

7.3.3 Technical Process as prototype for datafactory

This section shows the workflow happened on the first half part of the year of 2024.

Development Environment Setup

Database Creation

The structure of the database for GAN models includes four main folders:

trainA: Contains images for training domain A, acquired within the context of the R2DATO project.
trainB: Contains images for training domain B, also sourced from the R2DATO context.
testA: Contains images for testing domain A, coming from a different context related to R2DATO.
testB: Contains images for testing domain B, acquired from a different context within the R2DATO project. Each folder contains images relevant to the specific tasks of the model.

Data Preparation

The data were collected from various sources and prepared for model training. The following steps were followed:

Image Collection: Utilization of public datasets, field data collection, and generation of synthetic images.
Image Preparation: Cleaning, resizing, and annotating images. Image annotation is performed to provide accurate labels necessary for supervised model training.
Data Organization: Distribution of images into the trainA, trainB, testA, and testB folders. This systematic organization facilitates data loading during the training process and allows for effective model performance evaluation.

Models and Tools

For image generation, we explored several models, including GANs and diffusion models. Here is a description of the models, their architectures, and the advantages and disadvantages of each model.

DCGAN

The Deep Convolutional GAN (DCGAN) is an extension of GANs that uses deep convolutional neural networks to generate high-quality images. The architecture of DCGAN mainly consists of a generator and a discriminator, both composed of convolutional layers.

DDPM

The Denoising Diffusion Probabilistic Model (DDPM) is an image generation model based on the principle of reverse diffusion. The architecture of DDPM consists of a U-Net network for image generation.

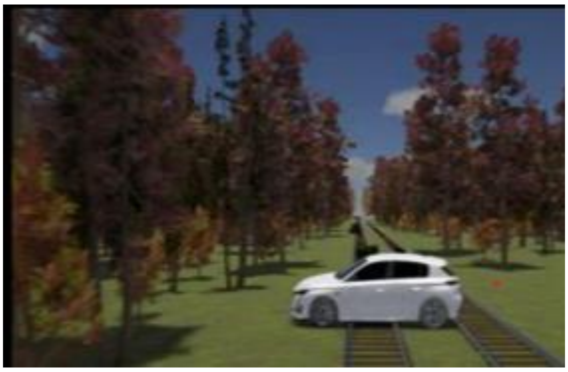


Figure 29 Original Image

Figure 30 Generated by DDPM

Models Used for Style Transfer

For style transfer, several models from the GAN family using various GitHub repositories have initially been explored. Here are some of the main models and their repositories:

CycleGAN: https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix
CUT (Contrastive Unpaired Translation): https://github.com/taesungp/contrastive-unpaired-translation
FastCUT: https://github.com/taesungp/contrastive-unpaired-translation
UNIT (Unsupervised Image-to-Image Translation Networks): https://github.com/mingyuliutw/UNIT
MUNIT (Multimodal Unsupervised Image-to-Image Translation): https://github.com/NVlabs/MUNIT
CycleGAN Turbo: https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix
U-GAT-IT: https://github.com/znxlwm/UGATIT-pytorch

CycleGAN

CycleGAN is a model that learns to translate images from one domain to another without requiring corresponding image pairs. It uses two generators and two discriminators.

CUT (Contrastive Unpaired Translation)

CUT introduces a contrastive method for learning unpaired translations by focusing on preserving content details.

Figure 31 Original Image

Figure 32 Generated by CUT

FastCUT

FastCUT is an optimized version of CUT that accelerates the training process by reducing the number of contrastive calculations.

UNIT (Unsupervised Image-to-Image Translation Networks)

UNIT uses an approach based on learning shared latent representations to translate images between domains.

MUNIT (Multimodal Unsupervised Image-to-Image Translation)

MUNIT enables multimodal translations by separating the content and style of images.

CycleGAN Turbo

CycleGAN Turbo is an improved version of CycleGAN with optimizations for speed and quality.

U-GAT-IT

U-GAT-IT uses attention-based unsupervised generative neural networks with adaptive layer normalization for image translations.

Advantages and Disadvantages

The following table provides a summary of the benchmarking performed on different artificial intelligence models. It compares performance in terms of image quality, training time, and the presence of artifacts for each model.

Model	Image Quality	Training Time	Presence of Artifacts
DCGAN	Low	Short	High
DDPM	High	Long	Low
CycleGAN	Medium	Moderate	Medium
CUT	High	Long	Medium
FastCUT	High	Short	Medium
UNIT	Medium	Long	Medium
MUNIT	High	Long	Low
CycleGAN Turbo	High	Moderate	Low
U-GAT-IT	High	Long	Low

Table 3 Comparison of AI Models: Image Quality, Training Time, and Artifact Presence

Use of Stable Diffusion

Diffusion models are a class of generative models that work by learning to reverse a diffusion process. These models have proven effective in generating high-quality images and videos with reduced artifacts. To improve results and control the style of videos as needed, the decision was made during the project to use stable diffusion models, promising better rendering, including:

SliceIt: https://github.com/fallenshock/Slicedit - SliceIt uses a stable diffusion architecture for generating stylized videos.

AnyV2V: https://github.com/TIGER-AI-Lab/AnyV2V - AnyV2V is designed for video-to-video translation using attention mechanisms.

TokenFlow: https://github.com/omerbt/TokenFlow - TokenFlow uses transformer networks for text-guided video generation.

Tune-A-Video: https://github.com/showlab/Tune-A-Video - Tune-A-Video allows adjusting the style of videos using variational autoencoders.

Video-P2P: https://github.com/dvlab-research/Video-P2P - Video-P2P uses attention propagation mechanisms to maintain temporal consistency in videos.

These models allow for the application and control of video styles but require considerable resources. Due to these demands, video generation is limited to a maximum duration of 8 seconds.

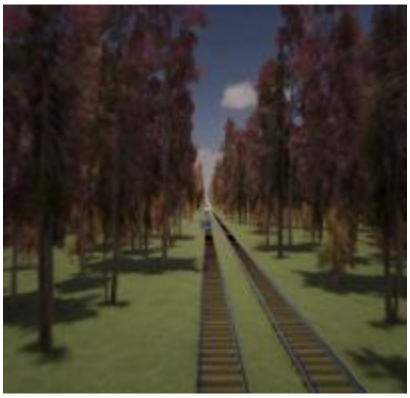


Figure 33 Original Image

Figure 34 Generated by SliceIt

7.4 First Results

After evaluating the advantages and disadvantages of the different models, each model was tested on a set of test images, including non-standard situations (NRS). These situations, derived from the analysis of an incident file provided by Transilien covering the period from 2021 to 2023, represent real-world scenarios involving various objects. This includes vehicles, pedestrians, animals, as well as unexpectedly placed objects such as refrigerators, shopping carts, and pallets, placed on tracks maliciously. These incident reports are presented as textual narratives written by SNCF agents and are never accompanied by images.

To simulate these scenarios faithfully and realistically, we used 3D assets and placed these objects in virtual environments. This process ensured that our tests accurately reflected objects as they are encountered in the field. The results obtained for each model thus provided a rigorous evaluation of their ability to handle complex and varied situations, contributing to the improvement of the accuracy of computer vision models used by SNCF.

The results show that each generative AI model has its own strengths and weaknesses. For example, the DDPM model produces high-quality images with few artifacts but requires a longer training time. In contrast, models like DCGAN train faster but generate images with more artifacts. The use of Docker not only facilitated the management of different configurations and software dependencies required to run the models but also ensured a consistent and reproducible testing environment.

One of the main advantages of using generative AI in this project is the significant time savings achieved by automating the generation of new images for datasets. This automation enabled rapid iterations and increased efficiency, which are crucial for meeting the dynamic needs of the project. Furthermore, thanks to these advanced techniques, we were able to simulate various environmental conditions such as rain, fog, and snow, thereby providing better preparation for models to function under different weather conditions. This ability to generate multiple and realistic environments is essential for testing and improving the robustness of computer vision models against varied terrain configurations and promises a demonstrated level of robustness, potentially certifiable by deployment.

Examples of transformation:

3D image true image mixed image

Figure 35 CycleGAN

Figure 36 SliceIt

7.4.1 Monitoring and Analysis of Loss Curves

The loss curves were analyzed over the progress of computations performed using style transfer with different GAN and Stable Diffusion models. The loss curves generally show the convergence of models over epochs[1]. Thus, we were able to compare the stability and consistency of the loss in different contexts, allowing a global estimation of the algorithms' effectiveness, which still need to be tested in the varied environments that the combination of (Simulation + Generative AI) promises to produce at scale.

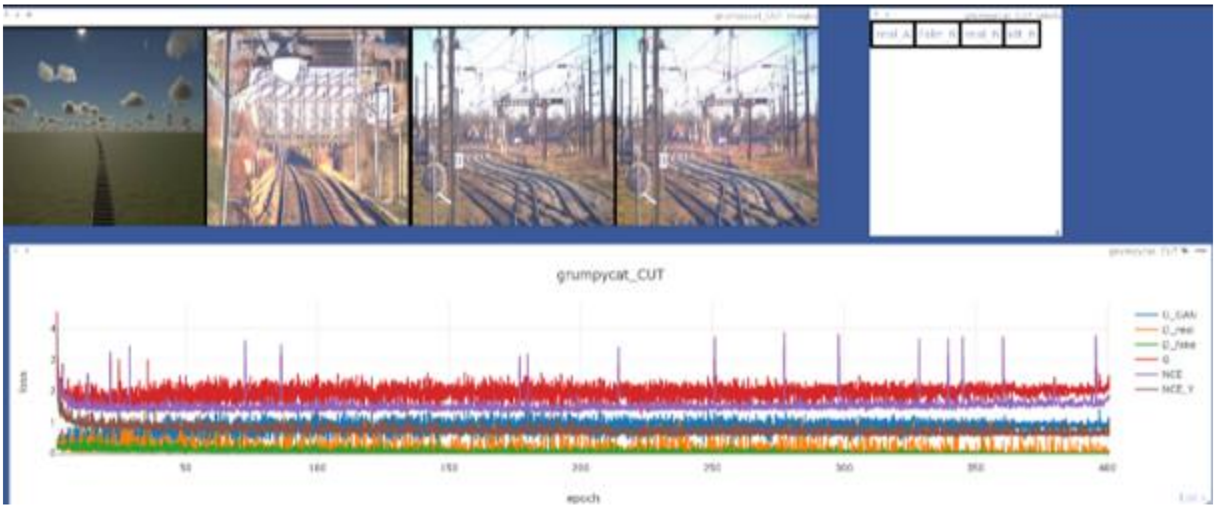


Figure 37 Analysis of Loss Curve Stability Across GAN and Stable Diffusion Models[20]

7.4.2 To sum up

This project has allowed for the exploration of various image generation and style transfer techniques to enhance railway environmental simulations, a major objective for the ERJU project. The main points addressed are:

Exploration of Image Generation Models

We utilized several GAN architectures, including DCGAN and DDPM, for image generation:

- Diffusion models, such as DDPM, demonstrated superior performance in terms of image quality, although they require longer training times.

Style Transfer

Several style transfer models were tested, including CycleGAN, CUT, and their variants.

Use of Stable Diffusion

Advanced stable diffusion models like SliceIt enabled the generation of high-quality videos:

- However, the duration of the generated videos is currently limited to 8 seconds due to available resources.
- The quality of videos generated by SliceIt was superior to that of videos generated by traditional GANs.

Optimization with DDP

The use of Distributed Data Parallel (DDP) optimized model training by distributing the workload across multiple GPUs:

- DDP significantly reduced training times, thereby improving the overall efficiency of the project.

Strategic Objectives

[20] These loss curves help us understand how models learn and adjust their parameters over time. Continuous decrease and stabilization of losses are positive indicators of the models' ability to perform effective style transfer.

Beyond the technical aspects, this project aligns with a broader strategy of the railway operator aiming to enhance safety and operational efficiency:

- Completing the Training Dataset: Augmenting the dataset with generated images and videos improves the models' ability to validate and test in the lab, ensuring better preparation before field implementation.
- Cost Reduction: By reducing the need for real data and accelerating development processes, the project contributes to lowering operational costs.
- Explainability and Certification: The use of generative AI facilitates model explainability, allowing for quicker certification by the railway operator, which is essential for regulatory compliance.
- Enhanced Trust: By increasing transparency and predictability of the models, trust in computer vision systems is strengthened.

In conclusion, the project has achieved many technical objectives but has also laid the groundwork for a potential new data infrastructure, aiming for greater robustness in intelligent vision systems and fostering a proactive approach to safety and innovation.

7.5 PROSPECTIVES

Extension of Video Duration

One of the main current limitations is the maximum duration of 8 seconds for generated videos. Future work could focus on:

- Optimizing resources or using computing clusters to extend this duration.

Improvement of Style Transfer Models

While current models have shown promising results, there is room for improvement:

- Integrating more advanced attention mechanisms or exploring new architectures could enhance transformation quality.

To bring more realism

Sim2real involves applying the style of a real image to a simulated one, making it appear as authentic as a photo or video captured by a camera. By aligning the visual characteristics of the simulated image with those of real-world images, this technique enables the use of these enhanced images as primary data. This approach bridges the gap between simulated and real data, making simulations more valuable for real-world applications and furthering the potential of AI and machine learning models trained on such data. The road to achieving this is still long, but the groundwork has been laid and the first hypotheses have been formulated, opening up new possibilities and requiring validation in future research efforts.

Application of Models

Models need to be tested on images produced by the combination of (Simulation + Generative AI) and the accuracy of predictions compared with natural and purely synthetic images to measure the level of algorithmic acceptability, which cannot be assessed solely by visual acceptability.

8 RESULTS AND DISCUSSION

8.1 FINDINGS FROM SIMULATION RUNS

Key Points:

- The simulation successfully implemented the requirements from multiple stakeholders.
- Demonstrated that the simulation environment and platform, as outlined in D7.1, are functional.
- Contributed synthesized data necessary for the D7.6 Open Dataset.
- Synthesized data is crucial because many Non-Regular Situations (NRS) cannot be recorded in the real world (fortunately). As accidents are rare, models must be trained on potential dangers using synthetic data.

The simulation project made significant strides in integrating the requirements of various stakeholders into a functional system. The primary accomplishment was demonstrating the real-world applicability of the simulation environment and platform, which was initially outlined in D7.1 as a theoretical concept. This practical demonstration validated that the platform is not only feasible but also effective in executing complex simulations that meet diverse needs.

Another key outcome was the successful generation of synthesized data, an important component for the D7.6 Open Dataset. This data serves as a substitute for real-world data, laying the groundwork for future model evaluations. Although model evaluation was beyond the scope of this deliverable, the synthesized data represents an essential first step in that direction. Synthesized data is crucial because many Non-Regular Situations (NRS) cannot be recorded in the real world due to the rarity and potential danger of such events. As accidents are fortunately infrequent, models must be trained on potential dangers using synthetic data.

Additionally, the qualification of AI systems requires massive amounts of data. Therefore, the simulated/synthetic data produced by the project is not only critical for model training but also forms the basis for AI homologation processes. This finding underscores the importance of synthesized data in ensuring that AI systems can be rigorously tested and qualified for real-world deployment.

The findings indicate that the simulation platform is capable of producing reliable and relevant data that can be used for various applications, including training and testing of machine learning models.

8.2 Implications for Real-World Application

Key Points:

- The generated data could be used for AI model evaluation, though this was not part of the current deliverable.
- Future steps involve comparing synthesized data with real-world data for validation of the digital sensor twins.

The implications of this simulation work extend far beyond the immediate project. The data generated, while not yet validated against real-world data, holds the potential to significantly impact how models are trained and evaluated in the future. One of the critical next steps is to compare the synthesized data with real-world data, which will help in assessing the accuracy of the digital sensor twins and applicability of the simulations. This comparison will require the development of specific metrics tailored to evaluate the fidelity of the simulation data. The synthetic data will serve as a reliable supplement for real-world data, thereby reducing the dependency on real-world testing, which is often costly and time-consuming. Moreover, synthetic data is indispensable for producing the high amounts of data required for approval of AI functions, and so it accelerates the development and deployment of new technologies, particularly in fields where real-world data is scarce or difficult to obtain.

8.3 Limitations and Challenges

Key Points:

- The trade-off between simulation detail and resource consumption (time, computing power).
- Limited availability of 3D assets.
- The focus was primarily on static objects due to the complexity in animating dynamic ones.
- The real-world sensor setup and its configuration is not fully developed; therefore the digital twins are subject to ongoing changes.
- The Validation of the created Dataset could be a challenge.

The simulation project faced several inherent limitations and challenges that influenced its outcomes. One of the most significant challenges was managing the trade-off between the level of detail in the simulation and the computational resources available. High-detail simulations require substantial processing power and time, both of which were limited. To manage these constraints, a notable example was the reduction of sensor resolution, which significantly decreased the data size and processing requirements. This compromise was deemed entirely acceptable as it adhered to the principle of being "as precise as necessary, not as precise as possible," ensuring that the simulation remained both efficient and effective. As a result, compromises had to be made, particularly in terms of the complexity and realism of the simulations. Another limitation was the availability of 3D assets, which restricted the range of scenarios that could be effectively simulated. The project also focused primarily on static objects due to the difficulties encountered in animating dynamic objects within the simulation environment. This focus on static scenarios, while necessary, limited the scope of the simulation's applicability to real-world situations where dynamic elements are often present. Additionally, replicating real-world hardware setups in a digital environment posed another challenge, particularly concerning the precise replication of digital twins of sensors and their exact positioning. This challenge is especially relevant for product development and homologation processes, where the accuracy of digital twins is crucial to ensure that the simulations accurately reflect the physical setups and their potential variations.

8.4 Future Work

Key Points:

- Incorporating dynamic objects in simulations.
- Evaluating and training models using the synthesized data.
- Addressing train traffic signal variations in simulations, which were not covered in the current dataset.
- Simulating environmental conditions like rain, fog, and their effects on sensors, particularly on lenses or windshields.
- The business model for offering simulations and synthetic data in the sector is currently being developed at DB InfraGO AG.

The future of this simulation project lies in addressing the limitations identified and expanding its capabilities. One of the most critical areas for future work is the inclusion of dynamic objects in simulations. The current focus on static objects limits the scope and applicability of the simulations, particularly in scenarios where movement and interaction are key factors. Additionally, there is a need to further utilize the synthesized data for its intended purposes, such as training and evaluating machine learning models. This will involve not only the use of the data but also the development of new methods and metrics for its evaluation. Another important area for future work is the simulation of train traffic signal variations, which was not addressed in the current dataset. Incorporating these variations will enhance the realism of the simulations and make them more applicable to a wider range of scenarios. Furthermore, an important addition to future simulations could involve simulating environmental conditions like rain, fog, and their effects on sensors. This would include challenges such as rain accumulating on lenses or windshields, which can significantly impact the performance of the sensors. As the project progresses, it will be essential to continuously refine the trade-offs between detail, resource use, and output quality to optimize the utility of the simulations for real-world applications.

DB InfraGO's simulation platform is being developed so that customers from the rail sector can request and obtain simulations and synthetic data, especially from non-regular sites (NRS).

8.5 Summary of Objectives and Achievements

Deliverable 7.3, titled "Perform Simulation with Initial Implementation of the Data Factory", is an important component of Task 7.2 under Work Package 7 (WP7) of the R2DATO project. The overarching objective of WP7 is to develop and implement a Data Factory capable of supporting automated perception and incident management systems within a GoA4 (Grade of Automation 4) rail operation environment. D7.3 specifically aimed to execute simulations using the initial implementation of this Data Factory, focusing on the synthesis of sensor data that is vital for AI training and validation processes.

The project successfully fulfilled the objectives outlined in D7.3. Through extensive simulations, the Data Factory demonstrated its ability to generate high-quality synthetic sensor data. This data is essential for the D7.6 Open Dataset, which will serve as a foundational resource for developing and validating machine learning models critical to autonomous train operations. The simulations adhered to the requirements defined in earlier deliverables, particularly D7.1, and provided valuable insights into the platform's real-world applicability.

8.6 Recommendations for Next Steps

Key Points:

- Develop metrics to validate simulation data against real-world data, accelerated by the open data set and the developer community.
- Utilize synthesized data for training and evaluation purposes.
- Expand simulation capabilities to include dynamic objects, weather conditions and more detailed signal processing.
- Sector initiative for joint simulation could be founded.

The immediate next steps should focus on validating the simulation data against real-world data. This validation is crucial for determining the accuracy and reliability of the simulations, and it will involve developing robust metrics specifically designed for this purpose. The open data set will contain the synthetic data, thus will accelerate this development through the participation of the developer community. Additionally, the project should continue to expand its simulation capabilities, particularly by incorporating dynamic objects and more detailed signal processing. These enhancements will make the simulations more realistic and applicable to a broader range of scenarios. Finally, as the project evolves, it will be important to continuously assess and adjust the trade-offs between detail, computational resources, and output quality. By doing so, the project can ensure that the simulations remain relevant and useful for their intended applications, whether in model training, evaluation, or other areas of research and development.

A sector initiative for joint simulation could be founded and would leverage synergy effects and accelerate the further development of the simulation platform and the development of GoA4 AI.

9 CONCLUSION

9.1 Contribution to New Knowledge

The work conducted in D7.3 makes a contribution to the knowledge base surrounding railway automation, particularly in the generation and application of synthetic sensor data. The Data Factory's ability to simulate Non-Regular Situations (NRS), which are challenging or impossible to capture in real life, addresses a key gap in current AI training methodologies. By providing large volumes of high-fidelity data, D7.3 supports the rigorous testing and homologation of AI systems, ensuring they are prepared to handle a wide range of scenarios, including those involving rare but critical events such as accidents.

This deliverable also advances the understanding of how simulated data can be used to supplement or replace real-world data in AI model training, particularly in safety-critical applications where data scarcity is a significant challenge. The successful implementation of the Data Factory in D7.3 lays the groundwork for future developments within the R2DATO project and the broader European rail system, contributing to the sector's ongoing digital transformation.

9.2 Main Findings and Implications

The main findings from D7.3 underscore the effectiveness of the Data Factory in producing relevant and reliable synthetic data for various applications within the R2DATO project. The simulations confirmed that the platform could meet the diverse requirements of stakeholders, demonstrating its potential for broader use in the rail industry. The synthesized data generated by the Data Factory is not only crucial for the D7.6 Open Dataset but also holds significant value for future AI model training and validation processes.

The implications of these findings are profound. The ability to simulate Non-Regular Situations and other complex scenarios allows for a more comprehensive approach to AI model development, reducing the reliance on real-world data collection, which can be limited by safety, cost, and availability constraints. The success of D7.3 suggests that synthetic data will play an increasingly important role in the development and deployment of autonomous train technologies, contributing to the overall goals of the Europe’s Rail System Approach.

9.3 Evaluation of Work Carried Out

The work carried out in D7.3 was both challenging and rewarding. The project faced several technical and operational challenges, particularly in balancing the level of detail in simulations with available computational resources. High-detail simulations required significant processing power and time, leading to necessary compromises such as reducing sensor resolution to manage data size and processing demands. While these compromises were justified to maintain efficiency, they also highlighted areas for future improvement, especially in simulating dynamic objects and accurately replicating real-world sensor setups.

Another notable challenge was the limited availability of 3D assets, which restricted the variety of scenarios that could be effectively simulated. The focus on static objects, while necessary, limited the scope of the simulations and their applicability to real-world situations where dynamic interactions are common. Despite these limitations, the achievements of D7.3 are significant, providing a robust foundation for future work within the R2DATO project and beyond.

9.4 Open Points and Proposals for Further Activities

Several open points and opportunities for further research have emerged from the work conducted in D7.3:

- **Incorporating Dynamic Objects**: Future work should prioritize the inclusion of dynamic objects in simulations. This will enhance the realism and applicability of the synthetic data, particularly for scenarios involving moving trains, obstacles, and other interactive elements.
- **Validation Against Real-World Data**: A critical next step is the validation of the synthesized data against real-world data. Developing specific metrics and methodologies for this validation process will be essential to ensure the accuracy and reliability of the simulation outputs.
- **Expansion of Environmental Simulations**: Future simulations should consider a broader range of environmental conditions, such as weather phenomena and their impact on sensor performance. Incorporating these factors will make the synthetic data more representative of real-world conditions, improving its utility for AI model training.
- **Development of a Business Model**: DB InfraGO AG is developing a business model to offer simulation services and synthetic data to the broader rail sector. This initiative could facilitate collaboration and innovation, particularly in generating and sharing synthetic data from Non-Regular Situations.
- **Sector-Wide Simulation Initiative**: Establishing a sector-wide initiative for joint simulations could leverage collective expertise and resources, accelerating the development of advanced simulation technologies. This initiative could also support the Europe's Rail System Approach by promoting standardization and fostering innovation across the industry.

9.5 Final Reflections

The work carried out in Deliverable 7.3 has made a substantial contribution to the R2DATO project, advancing the development of autonomous train technologies, and supporting the broader goals of digital transformation within the European rail sector. Despite the challenges encountered, the project successfully demonstrated the functionality and value of the Data Factory, laying the groundwork for future developments in AI model training and validation.

In conclusion, D7.3 not only fulfilled its stated objectives but also provided valuable insights and directions for future work. The deliverable's outcomes will continue to inform and guide the R2DATO project, ensuring that the technologies developed are robust, reliable, and ready for real-world deployment.

developer.blender.org. (29. August 2024). Von https://developer.blender.org/docs/?utm_medium=www-footer abgerufen

developer.nvidia.com. (29. August 2024). Von https://developer.nvidia.com/isaac/sim abgerufen

docs.foxglove.dev. (29. August 2024). Von https://docs.foxglove.dev/docs/introduction/ abgerufen

docs.omniverse.nvidia.com. (30. August 2024). Von https://docs.omniverse.nvidia.com/isaacsim/latest/features/sensors_simulation/isaac_sim_sensors_rtx_based_lidar.html abgerufen

docs.ros.org. (24. August 2024). Von https://docs.ros.org/en/humble/index.html abgerufen

dpa/cl. (26. April 2008). *welt.de*. Von https://www.welt.de/vermischtes/article1941644/ICE-entgleist-wegen-Schafherde-im-Tunnel.html abgerufen

Hollenstein, B. (05. May 2024). *20min.ch*. Von https://www.20min.ch/story/simplon-bls-zug-entgleist-auf-dem-weg-in-die-schweiz-103098533 abgerufen

leparisien.fr. (9. November 2008). Von https://www.leparisien.fr/faits-divers/des-tiges-de-fer-accrochees-aux-catenaires-09-11-2008-304326.php abgerufen

Lynn Sachs, M. D. (20. August 2021). *20min.ch*. Von https://www.20min.ch/story/zum-glueck-nicht-mein-arm-tuer-klemmt-tasche-ein-zug-faehrt-los-362473687679 abgerufen

ndr.de. (24. October 2022). Von https://www.ndr.de/nachrichten/niedersachsen/hannover_weser-leinegebiet/Zug-prallt-gegen-Einkaufswagen-auf-Schienen,aktuellhannover12024.html abgerufen

ots. (16. Mai 2022). *presseportal.de*. Von https://www.presseportal.de/blaulicht/pm/74168/5223528 abgerufen

radiohochstift.de. (24. January 2024). Von https://www.radiohochstift.de/nachrichten/paderborn-hoexter/detailansicht/bahn-entgleist-bei-bad-driburg-wegen-umgestuerztem-baum.html abgerufen

Rifflet, P. (2023. March 23). *actu.fr*. Von https://actu.fr/hauts-de-france/breuil-le-vert_60107/la-voiture-menace-de-tomber-sur-les-voies-les-trains-arretes-dans-l-oise_58452741.html abgerufen

schiene.de. (4. September 2022). Von https://www.schiene.de/news-2538/Ilztalbahn-kollidiert-mit-Gabelstapler.html abgerufen

SDA/nag. (28. October 2018). *https://www.bernerzeitung.ch/*. Von https://www.bernerzeitung.ch/nachtzug-von-berlin-nach-zuerich-rammt-baufahrzeug-928331466504 abgerufen

sony-semicon.com. (27. August 2024). Von https://www.sony-semicon.com/files/62/pdf/p-15_IMX490.pdf abgerufen

unity3d.com. (29. August 2024). Von https://docs.unity3d.com/Manual/index.html abgerufen