# 1 Description of the use case

## 1.1 Name of the use case

| ID | Application Domain(s) | Name of Use Case |
|---|---|---|
| UC2.Railway | Railway network | AI-assisted human re-scheduling in railway operations |

## 1.2 Version management

| Version Management | | | |
|---|---|---|---|
| **Version No.** | **Date** | **Name of Author(s)** | **Changes** |
| 0.1 | 04.03.2024 | Adrian Egli, Daniel Boos, Irene Sturm, Roman Ließner, Manuel Schneider, Julia Usher, Manuel Renold, Toni Wäfler, Samira Hamouche | Initial Version (import from UC2.Railway short) |
| 0.2 | 15.04.2024 | Anton Fuxjäger, Adrian Egli, Manuel Schneider, Julia Usher, Toni Wäfler, Roman Ließner, Cyrill Ziegler, Manuel Renold, Daniel Boos | Updated |
| 0.3 | 16.04.2024 | Ricardo Bessa | Revision |
| 0.4 | 25.04.2024 | Adrian Egli, Daniel Boos, Irene Sturm, Roman Ließner, Manuel Schneider | Final Revision |
| 0.5 | 30.05.2024 | Adrian Egli | Revision: Action space |
| 1.0 | 08.07.2024 | Ricardo Bessa | Final version |

## 1.3 Scope and objectives of use case

| Scope and Objectives of Use Case | |
|---|---|
| **Scope** | Traffic density on the European rail networks is constantly increasing. This increases the complexity of rail traffic management in operations: timetables are constructed to utilize the network's capacity maximally. At the same time, new construction or maintenance of railway infrastructure must be planned and carried out efficiently.<br>In railway operations, the already densely planned schedules are disturbed by unexpected events, such as delays, infrastructure defects, or short-term maintenance. The execution of the planned timetable can only be achieved by acting on these events by frequently adapting and re-scheduling the planned train runs. Already today, maintaining smoothly running operations requires that in operational centers, highly skilled personnel monitor the flow of traffic day and night and quickly make decisions about re-scheduling of trains. |
| **Objective(s)** | Aims to use AI-based methods to assist the human dispatcher in railway operations in re-scheduling train runs to fulfill all offered services and minimize delays for the customer (passenger). |
| **Deployment model** | Cloud services and on-premises. |

## 1.4 Narrative of use case

***Narrative of Use Case***

***Short description***

In railway operations, traffic on the network is planned to fulfill the intended service contracted with the Railway Undertaking Operating Managers (RUOM). In railway traffic operations, a pre-planned schedule is executed.

Unexpected events, such as infrastructure malfunctions or delays, occur. In this use case, a disruption or deviation occurs, and a dispatcher needs to become aware of the situation, analyze it, and decide to fulfill the requested services as close as possible to the pre-planned schedule. In our case, the dispatcher should be supported by an AI-assisted system to choose some actions, e.g., changing the speed, order, or trains routes. The support system takes the state of all trains in the dispatcher's control area as input and suggests options, i.e., sets of actions, to the dispatcher.

***Complete description***

Train dispatching is responsible for managing the movement of trains across a complex rail network. Human dispatchers rely on a computerized dispatching system to plan and monitor train movements. However, unexpected disruptions, such as signal failures, track blockages, or weather events, can cause significant delays and disruptions to the train schedule. In the event of a disruption, dispatchers need to quickly make decisions to reschedule trains and minimize the impact on passengers and freight. This can be complex and time-consuming, especially considering the intricate network of tracks, train priorities, and passenger demand.

In this use case, an AI-assistant system supports the human dispatcher. This system gets the real-time state of all the trains and tracks in the dispatcher's control area and derives possible dispatching options in case of deviations from the pre-planned schedule due to disruptions or delays. The options are presented in near real-time to the dispatcher and consist of a set of actions the dispatcher can perform to bring the trains back or close to their pre-planned schedules.

The following steps are performed in the use case:

1. **Definition of system parameters:** Detailed parameters are set for the pre-planned schedule, including the prioritization of trains in case of disruptions, acceptable delay margins, and specific criteria for train prioritization (e.g., passenger load and destination importance). This step also includes the configuration of safety systems, network capacity limits, and any special operational requirements unique to certain routes or times.
2. **Set up/configuration of human-AI teaming:** The human defines the boundary requirements, including the flexible allocation of decision-making authority between humans and machines.
3. **Schedule execution:** The initial operational plan is put into action. This includes the deployment of trains according to the pre-planned schedule, monitoring of train movements, adherence to the sequence of commercial stops, and ensuring compliance with operational requirements like safety systems and traffic density management.
4. **Monitoring:** At any time during operations, the human dispatcher can monitor the flow of traffic in the area of control. Visual displays of the traffic running through the network exist, and metrics are available. Information about the current intended plan is available.
5. **Detection of deviation:** At any time in operations, the human-AI team detects an emerging deviation of the actual state of the system from the planned state. The re-scheduling process can be initiated by various triggers such as infrastructure changes (e.g., blocked tracks, malfunctioning switches), train delays, equipment malfunctions, or potential future issues. The system is designed to detect these deviations in real time and assess their impact on the overall schedule. The system also predicts issues that might become relevant in the future.
6. **Action (re-scheduling):** Upon detecting a current or future deviation by the system or human, the system provides a detailed display of the issue, e.g., including its nature, location, and expected impact on the schedule. Either the human or the system starts with a suggestion, leading to two further paths of actions:
    a. The system provides suggestions. The human provides feedback (e.g., context unknown to the system). AI adapts the solution based on the feedback. The human agent can choose to select one of the suggestions by the AI systems, initiate a new solution search, or choose their own course of action.
    b. The human provides a suggestion. The AI system provides quantified feedback to the human suggestions, including own and adapted suggestions. Humans select one of the proposed solutions and initiate action. Alternatively, humans formulate a hypothesis, and the AI system provides evidence for and against these hypotheses.
7. **Execute solution:** The newly adapted schedule is implemented. The system continuously monitors for any further deviations and adjusts the schedule as needed to maintain operational efficiency and adherence to time constraints.

8. **Human review and system adjustment:** A human supervisor reviews the system's performance, analyzing how effectively it responded to deviations and the impact on service delivery. Based on this review, adjustments are made to the system's parameters, such as altering the prioritization criteria, adjusting acceptable delay thresholds, or refining the algorithm for schedule recalculations. This step ensures continuous learning and improvement of the system based on operational experiences and organizational goals.
9. **Co-learning:** AI agent learning loop using observations of the human decision-making process. The human learning process (e.g., to detect emerging deviations or to develop solutions) is explicitly supported by human-AI interaction.

### *Stakeholders*

**Railway network operator:** Operator of the railway network in charge of maintaining traffic flow on the railway network to provide high quality-of-service to their direct customers (RUOMs) and the passengers.

**Network supervisor:** Human supervisor of the automated railway system (something like the former dispatcher who is not dispatching himself anymore but monitoring the system state),

**RUOM:** Railway Undertaking Operation Manager offering passenger and freight traffic services.

**Neighboring areas of control/operational centers.**

**Passenger:** The primary end-user of the railway services whose travel experience and satisfaction are directly impacted by the efficiency and punctuality of train operations.

**Government and society:** The quality of railway services is a concern of the government and society.

### *Stakeholders' assets, values*

**Railway network operator:**

- Available capacity on the network: a low-quality re-scheduling functionality will consume more capacity on the network.
- Reputation: low performance of the AI system can lead to a bad reputation in terms of operational stability, punctuality, etc., which might cause customers to not rely on and to use less the services offered. This also concerns network operators, RUOM, and passengers.
- Legal and regulatory framework: Regulations with discrimination-free treatment of RUOMs.
- Unintended behavior of the AI system and actions by malicious actors can potentially compromise the safety of the train passengers, personnel on the train, and on and in proximity to the tracks, as well as infrastructure like tracks, power lines, tunnels, stations, etc.

**Human dispatcher:**

- Damage to the reputation as well as a potential general perception of an opaque AI system being in control of running trains can cause a decrease in the trustworthiness of the railway operator from a customer perspective, both for individual travelers and cargo transport.

The usefulness and understandability of the AI-system output to the dispatcher may influence the trustworthiness of the AI-system from the perspective of the dispatcher. Low trustworthiness might render the use of the AI system irrelevant as the dispatcher will not trust the options generated by the system, and the assumed benefit will not materialize.

### *System's threats and vulnerabilities*

**Trust from human operators:** The operational performance of the AI assistant will not be close to 100% of problems solved, which may hinder the confidence and trust of the human operator in the AI recommendations. This could introduce a negative cognitive bias in humans.

**Progressive deviation of environment behavior:** Not only can the system conditions evolve but also the operational rules, the human operators' behavior, or other applicable regulation. This can progressively alter the efficiency of the AI assistant if it is not regularly "updated". The issue can be exacerbated by the fact that such changes happen very incrementally in time and are quite hard to detect at the early beginning, where only a few changes should be adopted.

**A mismatch between AI training and deployment:** Where significant differences exist between the digital environment used to train the AI model or the lack of information in historical data used to train the AI model can cause issues under real operating conditions. This could lead to low robustness and poor performance during execution, e.g., recommendations based on inaccurate assumptions about observability and controllability.

**Security:** The AI system introduces the risk of malicious actors disrupting operations either through the disabling or disruption of the AI system or by influencing system to produce output that causes delays, etc

## 1.5 Key performance indicators (KPI)

| ***Name*** | ***Description*** | ***Reference to the mentioned use case objectives*** |
|---|---|---|
| Assistant relevance | Situation awareness of the human operator using the system It is based on an evaluation by the human operator of the relevance of action recommendations provided by the AI assistant and measured by the number of recommendations from the AI assistant effectively used by the human operator. | Linked to the capacity of the AI system to support the dispatcher in choosing some actions. |
| Human Information Processing | The volume of information that the human takes into account when making decisions with AI support (as compared to making decisions with no AI support). | Linked to the cognitive load of human dispatchers. |
| Punctuality | An aggregated measure of the delay in a scenario (defaults to be defined). | Linked to the objective of minimizing delays. |
| Response time | The time needed to produce a new schedule in case of a disturbance event. | Related to the objective of rapid re-scheduling. |
| Comprehensibility | It is defined as the ability to understand a decision logic within a model and, therefore, the ability to use this knowledge in practice (Futia and Vetrò, 2020).<br>Futia, G. and Vetrò, A. (2020). On the Integration of Knowledge Graphs into Deep Learning Models for a More Comprehensible AI. Information, 11 (2), 122-132.<br>Herm, L. V., Wanner, J., Seubert, F., & Janiesch, C. (2021). I Don't Get IT, but IT seems Valid! The Connection between Explainability and Comprehensibility in (X) AI Research. In ECIS. | Linked to interpretation of what has been learned and decision logic. |
| Acceptance | Acceptance of the system by a human user (e.g., Using the TAM model (technology acceptance model). | Reflects the reliability and trust of the AI system. |
| Trust towards the AI-Tool | *"(Dis)trust is defined here as a sentiment resulting from knowledge, beliefs, emotions and other elements derived from lived or transmitted experience, which generates positive or negative expectations concerning the reactions of a system and the interaction with it (whether it is a question of another human being, an organization or a technology)"* (Cahour & Forzy, 2009, p. 1261).<br>The human operators' trust towards the AI tool can be measured using the Scale for XAI (Hoffman et al., 2018) or similar. | Linked to the human operator's appropriate trust in the AI system as a necessary precondition of adequate use. |
| Human motivation | *"Intrinsic motivation is defined as the doing of an activity for its inherent satisfaction rather than for some separable consequence. When intrinsically motivated, a person is moved to act for the fun or challenge entailed rather than because of external products, pressures, or rewards"* (Ryan & Deci, 2000, p. 54).<br>The human operators perceived internal work motivation can be measured by using the Job Diagnostic Survey (Hackman & Oldham, 1974) or similar. The questionnaire needs to be adapted to the AI context (e.g., problem detection with AI-assistance). | This is linked to the necessary motivation of the human operator to use the AI for complete a task and reach corresponding objectives. |
| Human control/autonomy over the process | Autonomy is the degree to which the job provides substantial freedom, independence, and discretion to the employee in scheduling the work and in determining the procedures to be used in carrying it out" (Hackman & Oldham, 1975, p. 162). It consists of three interrelated | Linked to the perceived control of the human operator as a necessary prerequisite for |

| | | |
|---|---|---|
| | aspects centered on freedom in decision making, work methods and work scheduling (Morgeson & Humphrey, 2006). Parker and Grote (2022) view job autonomy interchangeably with job control.<br>The human operators perceived autonomy over the process can be measured by using the Work Design Questionnaire (Morgeson & Humphrey, 2006) or similar. The questionnaire needs to be adapted to the AI context (e.g. problem detection with AI-assistance). | taking responsibility for the efficiency and effectiveness of one's own work. |
| Human learning | Human learning is a complex process that leads to lasting changes in humans, influencing their perceptions of the world and their interactions with it across physical, psychological, and social dimensions. It is fundamentally shaped by the ongoing, interactive relationship between the learner's characteristics and the learning content, all situated within the specific environmental context of time and place, as well as the continuity over time (Alexander et al., 2009).<br>The human operators perceived learning opportunities working with the AI-based system can be measured by using the task-based workplace learning scale (Nikolova et al., 2014) or similar. The questionnaire needs to be adapted to the AI context. | Linked to the objective of mutual co-learning to assist human operator to improve his/her performance. |
| Decision support for the human operator | Decision support tools should be aligned with the cognitive decision-making process that people use when making judgements and decisions in the real world and ensure that the human operator retains agency (Miller, 2023). AI decision support tools should therefore help people to remain actively involved in the decision-making process (e.g. by helping them critique their own ideas) (Miller, 2023).<br>The decision support for the human operator can be measured based on the criteria for good decision support (Miller, 2023) or similar. The instrument needs to be further developed. | Linked to appropriateness of AI-based support of the human operator’s decision-making process. |
| Ability to anticipate | *“The ability to anticipate. Knowing what to expect, or being able to anticipate developments further into the future, such as potential disruptions, novel demands or constraints, new opportunities, or changing operating conditions”* (Hollnagel, 2015, p. 4).<br>The human operator’s ability to anticipate further into the future can be measured by calculating the ratio of (proactively) prevented deviations to actual deviations. In addition, the extent to which the anticipatory sensemaking process of the human operator is supported by an AI-based assistant can be measured by using the Rigor-Metric for Sensemaking (Zelik et al., 2010) or similar. The instrument needs to be further developed and adapted to the AI context. | Linked to AI-based enabling of human operator to minimize delays for the customers. |
| Situation awareness | “Situation Awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” (Endsley, 1988, p. 12).<br>The human operator’s situation awareness can be measured by using the Situation Awareness Global Assessment Technique (SAGAT) (Endsley, 1988) or similar. | Linked to the AI-based assistance of the human operator for developing an appropriate situation awareness. |

## 1.6 Features of use case

| | |
|---|---|
| ***Task(s)*** | Planning, prediction, optimization, interactivity, recommendation |
| ***Method(s)*** | Reinforcement learning has been applied to this use case, but other AI approaches are possible. |
| ***Platform*** | Flatland digital environment. |

## 1.7 Standardization opportunities and requirements

| ***Classification Information*** |
|---|
| ***Relation to existing standards*** |
| ***ISO/IEC 23894:2023****, Information technology — Artificial intelligence — Guidance on risk management*. Autonomous management and optimization of railway scheduling in real-time are high-stakes tasks, and therefore, risk management specifically related to AI is fundamental.<br>***ISO/IEC 38507:2022****, Information technology — Governance of IT — Governance implications of the use of artificial intelligence by organizations*. Autonomous AI requires an analysis of governance implications and also a redefinition of the organization structure.<br>***ISO/IEC 24029-2:2023****, Artificial intelligence (AI) — Assessment of the robustness of neural networks — Part 2: Methodology for using formal methods*. Since artificial neural networks can be a component of the autonomous AI system, formal methods to assess the robustness properties of neural networks are fundamental to certify and monitor autonomous systems.<br>In railway transport, there are different levels of automation (Grade of Automation, GoA) defined in the **IEC 62267** Standard ("Railway applications - Automated urban guided transport (AUGT) - Safety requirements”). This standard covers high-level safety requirements applicable to automated urban guided transport systems, with driverless or unattended self-propelled trains, operating on an exclusive guideway.<br>***DIN EN 50126****, Railway Applications – The Specification and Demonstration of Reliability, Availability, Maintainability and Safety (RAMS)*. It considers the generic aspects of the RAMS life cycle and provides a description of a Safety Management Process. It provides guidelines for defining requirements, conducting analyses, and demonstrating the reliability, availability, maintainability, and safety aspects throughout the lifecycle of railway applications.<br>***DIN EN 50128****, Railway applications – Communication, signaling and processing systems*. Outlines the procedural and technical criteria for crafting software intended for programmable electronic systems in railway control and protection applications. |
| ***Standardization requirements*** |
| Opportunities for standardization and deriving recommendations for critical operations management and support, especially regarding co-decision-making and human-computer interaction, as well as safety requirements. See also UC1.Railway. |

## 1.9 Societal concerns

| ***Societal concerns*** |
|---|
| ***Description*** |
| **Privacy and data protection:** The use of AI in railway scheduling involves the collection and analysis of large volumes of data, including potentially sensitive information. There is a concern about how this data is stored, processed, and protected, especially in compliance with data protection regulations like GDPR. Ensuring the privacy and security of passenger and employee data is paramount.<br>**Transparency and accountability**: There is a societal demand for transparency in how AI systems make decisions, especially in critical infrastructure like railway systems. The public might be concerned about the lack of understanding of AI decision-making processes and the accountability mechanisms in place in case of failures or errors.<br>**Employment and skill shift:** The automation of train scheduling might lead to concerns about job displacement and the need for reskilling of railway staff. While AI can optimize operations, it also changes the nature of work, requiring a shift in skills for human operators who now need to oversee and interact with advanced AI systems.<br>**Public trust and acceptance:** For the successful implementation of AI in public transportation, gaining and maintaining public trust is crucial. There may be apprehensions and resistance from the public regarding the shift to AI-driven systems, especially among those accustomed to traditional methods.<br>**Safety and security:** The use of AI-systems for critical operational scenarios raises concerns |

| |
|---|
| regarding the continued safety and security of these systems. Understanding failure modes, developing robust models, and ensuring resilience to adversarial attacks are among the many topics to be tackled.<br>**Inequality:** Such systems might introduce inequality in service quality for different geographic regions or categories of passengers due to the opacity of the system, bias and self-learning aspects. |
| ***Sustainable Development Goals (SDG) to be achieved*** |
| SDG9. Decent work and economic growth / SDG9. Industry, innovation and infrastructure / SDG11. Sustainable cities and communities / SDG13. Climate action |

## 2 Environment characteristics

| ***Data characteristics*** | |
|---|---|
| ***Observation space*** | Fully observable with limitations due to the unpredictable duration of delays and malfunctions.<br>Data update is near real-time (rather seconds than hours).<br>Domain: defined on a continuous space.<br>Size: Depending on the type of observation considered local or global the total size can depend, but will generally be very large.<br>Noise: The observation can be noisy due to the communication system and the various signaling devices (*signal box*).<br>(In addition to more than 10,000 trains (per day), there are over 32,000 signals and over 14,000 switches in the Swiss rail network. All of this information must be taken into account and observed, thus the global observation is very large.) |
| ***Action space*** | The action space of the environment is mixed. Actions like which route to take on a switch are discrete as well as decisions like if a train should accelerate or decelerate. However, dependent on the algorithmic approach, the rate of acceleration, deceleration, the velocity to move forward and similar can be modelled both discrete and continuously.<br>Also dependent on the algorithmic approach is the dimension of the action space. While the action space grows linearly with the number of trains for the algorithmic part, it grows exponentially if there is a central actor controlling all the trains. The action space of the human dispatcher is in any case exponentially growing with the number of trains.<br>Further, the dimensionality of the action space depends on infrastructure and timetable elements like switches, signals and scheduled stops. Hereby, the impact on the dimensionality of the action space depends not only on the nature of the actor in the algorithmic part but also on the type of task, i.e. if the task is tackled episodically or sequentially on the algorithmic side. For the human dispatcher, the task is generally considered to be sequential, since an action is usually dependent on previous actions taken.<br>Time horizon: for an action is typically from a few minutes to a couple of hours.<br>The action space of the flatland environment is 5 (go left, go forward, go right, stop, none). However, each train run (agent) must perform one of these basic actions at each decision point (time step). This means that the total number of actions to be selected is very large and stays in linear relation to the number of agents - i.e. in a problem-solving scenario with n agents and m time steps, the actions should be chosen in such a way that the combination of selected actions leads to the desired outcome or optimal solution. Each agent has a set of a actions to choose from, from which they must select one at each time step. Therefore, the solution involves n x m x a possible actions. (Up to 800 trains run simultaneously on the Swiss rail network. In many cases they interact directly or indirectly with each other.) |
| ***Type of task*** | The nature of the task depends on the algorithmic approach. While AI models can determine which action to take fully based on the current state without including information about past actions and would therefore be considered episodic, other approaches can, to a large degree, approach the problem-solving as a sequential task, for example, if planning is involved. The human dispatcher usually approaches the task sequentially. |
| ***Sources of uncertainty*** | Stochastic, with the following sources of uncertainty:<br>1) Weather conditions can impact, e.g. the friction of wheels on rails which leads to different acceleration and deceleration behavior.<br>2) The travel demand influencing both the total load of a train and the delay to board other passengers. |

| | |
|---|---|
| | 3) Disruptions: Train level – locomotives or other rolling stock issue that may arise and results into a delay; Infrastructure level – signal malfunctions or construction sites.<br>4) Sensors and communication level – a failure may introduce noise and uncertainty in the observation of the environment. |
| ***Environment model availability*** | A specific model of the environment is not available. Although a good approximation of it can be achieved as the basic laws of physics are defined and clear. However, a model of the environment will be simplified in general and subject to uncertainty (see above). |
| ***Human-AI interaction*** | Co-learning between the human and AI: The interaction between humans and AI is crucial in this specific use case. The use case allows for bidirectional communication in the decision-making problem, enabling humans to both use the system as a supporting tool for making decisions and to provide additional context and feedback to the AI to make the decision. |

# 3 Technical details

## 3.1 Actors

| ***Actor Name*** | ***Actor Description*** |
|---|---|
| Dispatcher | The dispatcher is a human responsible for monitoring and analyzing railway traffic. The main role is to ensure the safe and efficient movement of trains by controlling the flow of traffic and making decisions based on real-time information. The dispatcher determines the order of trains and may deviate from planned routes when necessary to accommodate unexpected situations or optimize the overall operation. The decisions play a crucial role in maintaining the smooth functioning of the railway system. |
| Traffic control system | The traffic control system collects information such as traffic signals, train positions, and current train speeds and also provides a human-machine interface for controlling ongoing traffic. The system's goal is to manage the flow of traffic efficiently, centrally, and safely. This necessitates the comprehensive collection of available information to effectively support the decision-making process, which is primarily performed by human dispatchers. Consequently, the traffic control system is vital and should be implemented with a human-centered approach unless a fully automated solution is available. |
| Train run (Driver) | A train run refers to the operation of a train on a specific route or journey from one station to another. It encompasses the entire process of a train traveling along its designated path, including departure from the originating station, intermediate stops (if any), and arrival at the destination station. The current position and speed of the train are communicated to the traffic control system. |

## 4 Step-by-step analysis of use case

### 4.1 Overview of scenarios

| Scenario conditions | | | | | |
|---|---|---|---|---|---|
| **No.** | **Scenario name** | **Scenario description** | **Triggering event** | **Pre-condition** | **Post-condition** |
| 1 | Reactive Re-Scheduling | The reactive re-scheduling by the human-AI team once a deviation or disturbance has already occurred. | An emerging disruption or deviation occurring (e.g.. blocked track, malfunction train) | Intended service: a set of train runs with Start- and end location, a sequence of commercial stops, both with time information (Latest arrival, minimal dwell time, earliest departure).<br>An initial (microscopic) operational plan that is executable and fulfils the intended services such as the arrival and departure times of trains at commercial stops. | System has produced a new operation plan that is executable in the simulation and leads to an "acceptable" state at the end of the scenario |
| 2 | Co-learning for reactive re-scheduling | The co-learning process initialized by the reactive re-scheduling by the human-AI team once a deviation or disturbance has already occurred. | Human and AI action and interaction during the re-scheduling process occurring after a disruption or deviation. | Initial human expertise and initial AI model required for corrective problem solving (e.g. solution generation). | Improved human expertise and/or improved AI model required for corrective problem solving.<br>The improvement was the result of human-AI interaction explicitly supporting the human's and/or the AI's learning processes. |
| 3 | Proactive re-scheduling | Proactive re-scheduling by the human-AI team upon detection of weak signals. | Detection of precursors or weak signals indicating a probability of larger disruptions and deviation in the future | Intended service: a set of train runs with Start- and end location, a sequence of commercial stops, both with time information (Latest arrival, minimal dwell time, earliest departure).<br>An initial (microscopic) operational plan that is executable and fulfils the intended services such as the arrival and departure times of trains at commercial stops. | System has produced a new operation plan that is executable in the simulation and leads to an "acceptable" state at the end of the scenario without the presence of any additional weak signals. |
| 4 | Co-learning for proactive re-scheduling | Co-learning process initialized by the proactive re-scheduling By the human-AI team | Human and AI agent action and interaction during the detection and rescheduling phases. | Initial human expertise and initial AI model required for preventive problem solving (e.g. problem detection, identification of leverage points). | Improved human expertise and/or improved AI model required for preventive problem solving.<br>The improvement was the result of human-AI interaction explicitly supporting the human's and/or the AI's learning processes. |

### 4.2 Steps of scenario

| Step no. | Event | Name of process/ activity | Description of process/ activity Service | Information producer (actor) | Information receiver (actor) | Information Exchanged | Requirement |
|---|---|---|---|---|---|---|---|
| 1 | Start | Definition of system parameters | Detailed parameters are set for the pre-planned schedule, including the prioritization of trains in case of disruptions, acceptable delay margins, and specific criteria for train prioritization (e.g., passenger load, destination importance). This step also includes the configuration of safety systems, network capacity limits, and any special operational requirements unique to certain routes or times. | Administrator | Network Operator | SYSPAR | |
| 2 | System params defined | Set up / configuration of human-AI teaming | The human defines the boundary requirements, including the flexible allocation of decision-making authority between human and machine. | Dispatcher | AI Assistant | CONFIG | |
| 3 | Teaming initialized | Schedule execution | The initial operational plan is put into action. This includes the deployment of trains according to the pre-planned schedule, monitoring of train movements, adherence to the sequence of commercial stops, and ensuring compliance with operational requirements like safety systems and traffic density management. | Dispatcher | TMS | EXECPLAN | |
| 4 | Information presented | Monitoring | At any time in operations the human dispatcher can monitor the flow of traffic in the area of control. There exist visual displays of the traffic running through the network and in addition metrics are available. Information about the current intended plan is available. | AI Assistant | Dispatcher | STATE | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 5 | Deviation detected | Detection of deviation | At any time in operations an emerging deviation of the actual state of the system from the planned state is detected by the human-AI team. The re-scheduling process can be initiated by a variety of triggers such as infrastructure changes (e.g., blocked tracks, malfunctioning switches), train delays, equipment malfunctions or potential future issues. The system is designed to detect these deviations in real-time and assess their impact on the overall schedule. The system also predicts issues that might become relevant in the future.<br>For scenarios 1 and 3, this step consists of **detecting** deviations (reactive) which have already occurred. In scenarios 2 and 4, the human-AI team **predict** (proactive) potential deviations. These detected / predicted deviations then trigger re-scheduling. | AI Assistant/ Dispatcher | Dispatcher / AI Assistant | DEVINFO | |
| 6 | Suggestion provided | Re-scheduling suggestion | Upon detecting a current or future deviation by the system or human, the system provides a detailed display of the issue, including its nature, location, and expected impact on the schedule. Either the human or the system starts with a suggestion, leading to two further paths of actions:<br>The system provides suggestions. The human provides feedback (e.g., context that is not known to the system). AI adapts the solution based on the feedback. The human agent can choose to select one of the suggestions by the AI systems, initiate a new solution search, or choose their own course of action.<br>The human provides a suggestion The AI | AI Assistant/ Dispatcher | Dispatcher / AI Assistant | RESUG | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | system provides quantified feedback to the human suggestions, including own and adapted suggestions. Human selects one of the proposed solutions and initiate's action. Alternatively, the human formulates hypothesis, the AI system provides evidence for and against these hypothesis. | | | | |
| 7 | Suggestion received | Execute solution | The newly adapted schedule is then put into operation. The system continuously monitors for any further deviations and adjusts the schedule as needed to maintain operational efficiency and adherence to time constraints. | Dispatcher | TMS | RESCHED | |
| 8 | New schedule put into operation | Human review and system adjustment | A human supervisor reviews the performance of the system, analyzing how effectively it responded to deviations and the impact on service delivery. Based on this review, adjustments are made to the system's parameters, such as altering the prioritization criteria, adjusting acceptable delay thresholds, or refining the algorithm for schedule recalculations. This step ensures continuous learning and improvement of the system based on operational experiences and organizational goals. | AI Assistant | Dispatcher | REPORT | |
| 9 | Observations batch recorded / Training session | Co-learning | For scenarios 3 and 4, an additional co-learning loop occurs, consisting of a loop on the side of the AI agent and one on the side of the human agent.<br>AI agent learning loop uses observations of the human decision-making process to improve its own decisions. Human learning process (e.g., to detect emerging deviations or to develop solutions) is explicitly supported by human-AI interaction. | TMS | AI Assistant / Dispatcher | OBS | |

## 5 Information exchanged

| ***Information exchanged*** | | |
|---|---|---|
| ***Information exchanged (ID)*** | ***Name of information*** | ***Description of information exchanged*** |
| | | |
| SYSPAR | System Parameters | Series of parameters necessary to initialize the environment and providing all operative information to the agent(s). |
| CONFIG | Configuration of human-AI teaming | Parameters defining the "work agreement" between the AI and human agent, for example the allocation of decision authority. |
| EXECPLAN | Operational plan | Planned schedule to be executed, including information such as commercial stop sequence and operational requirements. |
| STATE | State of the system | Detailed information on the current state of the system. |
| DEVINFO | Devion information | Detailed information on the deviation, including its nature, location, and expected impact on the schedule. |
| RESUG | Re-scheduling suggestions | Suggestion for rescheduling actions developed by the AI agent – e.g. list of actions to take in the next update cycles |
| RESCHED | New operational plan | New schedule developed by the human-AI team. |
| REPORT | Report of adjusted plan performance | Detailed performance report of system performance after executing the new operational plan, provided by the AI agent. |
| OBS | Recorded observations | Series of rescheduling events and states including eg. trainrun position, ., trainrun running state such as malfonctioning or good |

## 6 Requirements

| **Requirements** | | |
|---|---|---|
| **Categories ID** | **Category name for requirements** | **Category description** |
| Ro | Robustness | Encompasses both its technical robustness (ability of a system to maintain its level of performance under a variety of circumstances) as well as its robustness from a social perspective (ensuring that the AI system duly takes into account the context and environment in which the system operates). This is crucial to ensure that, even with good intentions, no unintentional harm can occur. *Source: EU-U.S. Terminology and Taxonomy for Artificial Intelligence. First Edition* |
| E | Efficiency | Ability of an AI system to achieve its goals or perform its tasks with optimal use of resources, including time, computational power, and data. |
| I | Interpretability | Make the behavior and predictions of AI systems understandable to humans, i.e., degree to which a human can understand the cause of a decision. *Source: Molnar, Christoph. Interpretable machine learning. Lulu. com, 2020.* |
| Re | Regulatory and legal | The AI system's capacity to meet its objectives while complying with relevant laws, regulations, and standards. |
| Fa | Fairness | Ensure the recommendations and predictions of the AI system are in line with the principles of fairness (i.e., fair distribution of the benefits and strain/harm) |
| O | Other | Other non-function requirements related to environmental concerns and maintenance |
| **Requirement** | **Requirement name** | **Requirement description** |

| R-ID | | |
|---|---|---|
| Ro-1 | Reasonable recommendations in new situations (not seen during model training) | Systems provides reasonable solutions for situations not seen during training. |
| Ro-2 | Good performance in operating scenarios with high variability | System performs well in situations with many fast-changing elements. |
| Ro-3 | Retrospective quality control | Quality of provided options can be assessed in retrospect. |
| E-1 | Capacity to handle operating scenarios with high complexity | System derives options fast and with high quality in complex situations with many trains, switches and other elements involved. |
| E-2 | Scalability | Concerns the system's ability to handle growth, such as increased train traffic or network expansion, without performance degradation. This ensures the system remains effective as the scale of railway operations increases. |
| E-3 | Generalization to different scenarios | The system’s ability to handle previously unseen scenarios and generalize to areas of observation and action space not visited during training (e.g., different speed profiles, rails configuration etc.) |
| I-1 | Interpretability of suggestions | The process through which the AI system learns and operates, including how it generates suggestions, is transparent and understandable to the human dispatcher. Further, the decision making that leads to the suggestion as well as its limitations are explained to the human dispatcher. |
| Re-1 | Compliance with legal standards and regulations | Adherence to data protection laws, safety regulations, cybersecurity, and ethical guidelines governing AI systems in public transportation and the EU AI Act. |
| Fa-1 | Distribution of Delays | The system can be analysed to understand the distribution of delays according to certain fairness criteries (eg. region, RUOMs, groups, individuals) and allows to take measures to increase the fair distribution of delays. |
| Re-2 | RUOM Favouritism | The system should not unfairly favour specific RUOMs. Re-scheduling in railway operations must impact the RUOMs according to official policy. Measures should be put in place to ensure that these constraints are observed. |
| O-1 | Maintainability | Involves the ease with which the system can be maintained and updated. This includes the ability to diagnose and fix issues, update software, and adapt to changing operational requirements. |
| O-2 | Environmental Sustainability | Addresses the system's impact on the environment. This includes considerations such as energy efficiency of the AI algorithms, and the broader ecological footprint of the system's implementation and operation. |

## 7 Common Terms and Definitions

| Common Terms and Definitions | |
|---|---|
| **Term** | **Definition** |
| Railway Undertaking Operating Managers (RUOMs) | Company or organization that operates trains or provides rail transport services. |
| Traffic Management System (TMS) | Provides permanent control across the network, automatically sets routes for trains and logs train movements as well as detects and solves potential conflicts. |
| Co-learning | Co-learning indicate that human or AI in a team has the ability that can interact and learn from/with, and grow with their collaborator. The goal of co-learning is to support two dynamic growing entities to build |

| | |
|---|---|
| | mutual understanding, facilitate mutual benefit, and enable mutual growth over time. *Source: Huang, Y. C., Cheng, Y. T., Chen, L. L., Hsu, J. Y. J. (2019). Human-AI Co-learning for data-driven AI. arXiv preprint arXiv:1910.12544.* |
| Trains re-scheduling | Monitoring the movement of trains on a railway network and reacting to unexpected events, such as signal failures, track blockages, or weather events that disrupt operations, to other significant delays, and proactively to predicted deviations that affect planned operations. Re-scheduling measures include changing a train’s speed, path, or platform for stopping. |