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# Cooperation between a human traffic manager and an AI assistant for an improved railway infrastructure resilience

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**Abstract.** This article deals with railway traffic management, which includes tasks such as traffic planning, resource allocation, service adaptation and passenger information. Operators monitor the real-time movement of trains, passengers and resources, mitigate unexpected events and ensure safety. Human operators currently perform these complex tasks using their expertise. However, technical aspects of railways and concurrent disturbances increase cognitive load and biases, affecting traffic management and passenger satisfaction. To address these challenges, we propose an AI-based railway traffic manager assistant that combines Machine Learning (ML) and Human-Machine Interaction (HMI) to support operators in their daily tasks and assists them to make decisions when facing critical situations. This article outlines the design approach and introduces the initial assistant version. User-centred evaluation yields preliminary results from limited-scale experiments.

**Keywords:** Railway Operations, Resilient Systems, Decision Support, Reinforcement Learning, HMI, Cognitive Workload

## 1 Introduction

Operational rail supervision consists in monitoring traffic, anticipating disruptions and reducing their impacts. It aims at ensuring the resilience of the railway operations and the quality of passenger information. In this project, we are particularly interested in the supervision of passenger train movements. Trains, resources and passenger information must be monitored in real-time over a large area. Services must be adapted when disruptions occur. To carry out this activity, operators: (i) utilise situational awareness tools (e.g. real-time train location, passenger information); (ii) ponder various mitigation scenarios (e.g. delaying or canceling some trains, transferring passengers to another train); and (iii) make collaborative decisions regarding the ultimate course of action. According to [6], performance depends on the complementarity between operators, operational tools, and the working environment. In France, the current work environment

design relies on verbal exchanges and numerous tools (see [9]). Human operators must then aggregate and digest large amounts of information. While the process is time-consuming and mentally demanding, decisions must be taken rapidly. Furthermore, incidents tend to propagate. In this context, the mental load may hamper operators in understanding the overall situation [5] and act [7,1].

Operational disruptions cannot be solved following a pre-established plan: mitigation rather involves exploring a set of strategies and balancing their characteristics (e.g. impact on passengers, delays). Tools based on operational research have already been developed, but fail to match completely the needs of the operators. For instance, the strategies automatically suggested are not always understood by an operator, who may reason differently. Moreover, these algorithms rarely capture human expertise and seldom allow to share experience feedback when similar situations occur [12].

For these reasons, user-centred design seems more relevant to create efficient decision support tools. Following the progress of ML on cognitive tasks, we decided to create an AI-based assistant that leverages state-of-the-art RL algorithms and includes bidirectional features. In this paper, we introduce an AI-based assistant for railway traffic management that should (1) provide the user with comprehensive insights on the situation ; (2) quickly process the most demanding parts of the decision-making ; (3) learn both from real-life samples and from the experience of the operator it assists ; (4) investigate unexplored contingency plans.

## 2 Related works

Several studies have been conducted in the field of railway supervision, such as research on real-time rescheduling [2] and rescheduling through stop-skipping [3] in densely populated railway systems. In other studies, the promise of AI, especially Deep Reinforcement Learning (DRL), in the context of railway planning and scheduling was acknowledged. In general, DRL merges the capabilities of deep learning (DL), able to handle complex and vast problems, with reinforcement learning (RL) a generic and flexible framework for making sequential decisions. This integration introduces a new and potent AI tool that is increasingly gaining traction in the domains of autonomous decision-making and operational control. In particular, DRL can be highly beneficial in the domain of transportation systems, specifically in traffic management systems by automating numerous road control strategies, such as speed limit control, ramp metering, lane pricing, etc., which in turn enhances highway safety and mitigates congestion [4]. Other methodologies demonstrated that DRL agents excel at dynamic real-time rescheduling. In [8], the authors proposed a multi-agent deep reinforcement learning-based approach with different state representational choices to solve the real-time railway rescheduling problem by comparing three environment representation methods and three different solutions. In [11], Ning et al. proposed a solution to minimise the average total delay for all trains along the railway line where an agent is responsible for adjusting running time and generating instructions of departure sequences, aiming to maximise passenger

satisfaction and minimise the average total delay for all trains along the railway line. The learning agent is responsible for adjusting train travel times, waiting times and departure sequences, and conflicts are resolved simultaneously.

### 3 Research background

In this section, we focus on defining the main research topics of our study, i.e. Bidirectionality and Reinforcement Learning.

**Bidirectionality** Our design approach aims to (1) promote collaboration between the AI assistant and the human operator, (2) centralise expert knowledge for sharing and training. We explore the concept of *bidirectionality* to favor mutual learning between the AI assistant and its user. A literature review revealed two core features: *bidirectional learning* and *knowledge transfer*. Figure 1 depicts how we have implemented bidirectionality using RL.

*Bidirectional learning* enhances collaboration through a simultaneous exchange of behaviors and mental models. It involves two phases: communication and interaction. In the former, each agent explicitly shares its understanding, state and intentions [13]. In the latter, agents adapt their behavior to each other based on ongoing interaction and dynamic mutual understanding.

*Knowledge transfer* explores how a neophyte agent can absorb the experience of an expert agent [14]. This concept extends to human-machine interactions, regardless of who acts as the expert. Scenarios include distilling domain expertise to an AI that shares it back to untrained operators.

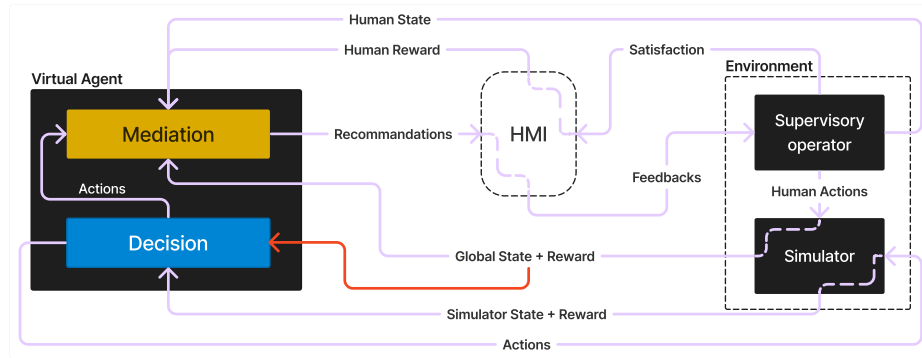


Fig. 1: Bidirectional interactions between our assistant and a human operator. The decision block ensures knowledge transfer. The mediation block enables bidirectional learning. Both components are trained using RL.

**Reinforcement Learning (RL)** [15] is a type of machine learning paradigm where an agent learns by interacting with its environment to achieve a specified

goal. The foundational principles rest on the agent making sequences of decisions, receiving rewards or penalties as a feedback, and refining its strategies or exploring others to optimise future rewards.

At its core, RL involves the agent observing the current state  $s$  of the environment, choosing an action  $a$ , based on a policy, and then receiving a reward  $r$  from the environment. The goal of the agent is to find an optimal policy that maximises the expected cumulative reward over time.

Function approximation – particularly using deep neural networks (often referred as Deep Reinforcement Learning or DRL) – has made RL applicable to complex tasks involving large state and action spaces. Our model, which includes a railway environment simulator, uses DRL to capture intricate patterns and relationships, allowing our AI assistant to generate nuanced strategies, tailored to the specificities of traffic management.

An RL agent can leverage the expertise of the human operator as additional knowledge during its training phase. By observing the actions and decisions made by the human operator, the agent can derive insights into efficient strategies. Conversely, the strategies discovered by the RL agent can enrich the decision-making of the human operator. This reciprocal learning encapsulates the core of bidirectionality.

## 4 An AI-based bidirectional assistant

The assistant we designed relies on a multi-services platform fed in real-time by Flatland simulator [10]. Figure 2 shows the main services of our assistant: (1) connectors to receive events and context from Flatland; (2) a service that notifies about failures, real-time train positions and statuses (3) an event and context tracker, that feeds our training dataset; (4) a recommender that provides mitigation strategies based on RL.

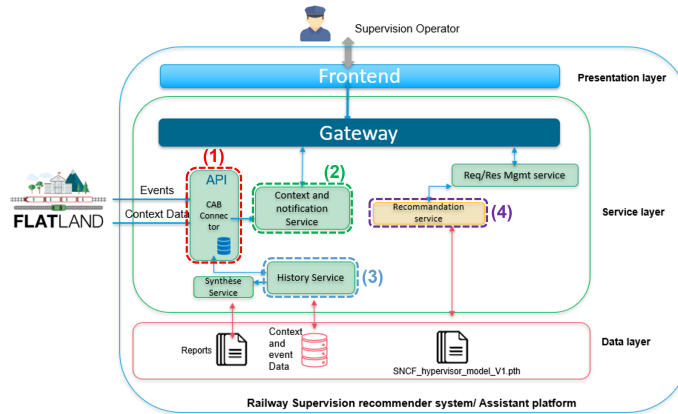


Fig. 2: Assistant architecture

To favor bidirectional interactions, we designed our user interface following the user-centred approach [16]. Workshops were organised to involve operators in the design process. As a guidance, we proposed to split the user interface into four zones (see Figure 3): (1) a list of the pending events pushed by Flatland; (2) a spatial visualisation of the context with the position of the trains; (3) a panel of mitigation strategies for a given event and their performance (e.g. delays, costs); (4) a temporal visualisation of the events. Through zone (3), the operator can request recommendations to the assistant, and choose or amend them. The proposal guidance is approved by end-users at a validation workshops.

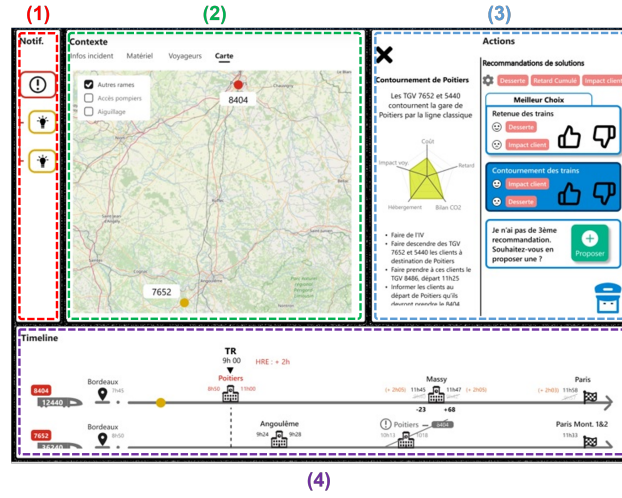


Fig. 3: Assistant HMI

## 5 Conclusion

In this paper, we described a virtual assistant we have designed to help traffic managers mitigate disruptions more efficiently and more rapidly. We presented the specific needs of the human operators and proposed guidelines to match them. The tool we designed leverages the most recent progress in RL and is inspired by the concept of bidirectionality. As a result, it allows (1) to learn from experts, (2) to distillate knowledge to neophytes, and (3) to adapt its policy recommendations to the human operator it interacts with.

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