Recommendations and Roadmaps Towards Intelligent Railways

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Abstract. This paper provides an overview of the main results achieved within the Horizon 2020 Shift2Rail project named RAILS (Roadmaps for Artificial Intelligence Integration in the Rail Sector). The RAILS roadmapping process provided state-of-the-art, taxonomy, future research directions, and recommendations in three macro areas: Railway Safety and Automation, Predictive Maintenance and Defect Detection, and Traffic Planning and Management. RAILS findings shed light on the potential of intelligent technologies and provided essential guidelines for integrating machine learning into next-generation smart railways.

Keywords: Artificial Intelligence · Machine Learning · Autonomous Trains · Smart Maintenance · Train Delay Prediction

1 Introduction

To the best of our knowledge, RAILS has been the first international research project investigating the potential and limitations of Artificial Intelligence (AI) in railways, with the goal of *providing recommendations for next-generation railways and contributing to the definition of roadmaps for future research*. In

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RAILS, we addressed three main areas: Railway Safety and Automation (WP2), Predictive Maintenance and Defect Detection (WP3), and Traffic Planning and Management (WP4). Through relevant case studies, we have shown the practical usage of machine learning with appropriate datasets for AI training and testing.

In this work, we summarise the project's main findings and provide pointers to relevant deliverables and technical papers where the reader can find further details that could not fit into this paper due to page limitation.

2 The RAILS Roadmapping Process and Outcomes

In RAILS, we focused on developing roadmaps for strategic planning [1] for each of the technical work packages (i.e., WP2, WP3, and WP4). Table 1 provides a mapping between the roadmap steps, the project outcomes, and related publications (deliverables[1] and technical papers).

In the first phase of the roadmapping process (WP1), we defined a reference taxonomy for AI in railways and analyzed the State-of-the-Art of scientific literature and worldwide projects, and the State-of-Practice through a survey involving stakeholders (Steps 1 and 2 in Table 1).

Following the outcomes of the first phase, two pilot case studies were identified for each technical WP (Step 3 in Table 1):

- *WP2*: "Vision-based Obstacle Detection on Rail Tracks" and "Cooperative Driving for Virtual Coupling of Autonomous Trains";
- *WP3*: "Smart Maintenance at Level Crossings" and "AI-based Rolling Stock Rostering";
- *WP4*: "Primary Delay Prediction" and "Incident Attribution Analysis".

For each case study, an experimental Proof-of-Concept (PoC) has been provided to investigate AI applications (Steps 4, 5, and 6 in Table 1), including unsupervised Deep Learning (DL) for anomaly detection on rail tracks, Deep Reinforcement Learning for intelligent control in Virtual Coupling, and DL-based Graph Embedding techniques for train delay prediction.

In the following, research directions resulting from the RAILS roadmapping process are presented, namely: Fully Autonomous Trains in Open Environments (Sect. 3); Intelligent Infrastructure Inspection (Sect. 4); and Route-based Arrival Delay Prediction on Services Level (Sect. 5).

3 Fully Autonomous Trains in Open Environments

In RAILS, we investigated the use of AI in *open environments* compared to *segregated environments* (i.e., railway tracks protected through physical barriers) [2]. We addressed the threats affecting safety that can be mitigated using appropriate Safety Envelopes [3]. In this context, the RAILS project addressed the main challenges listed below.

[1] Deliverables are available at: https://rails-project.eu/downloads/deliverables.

Table 1. RAILS Roadmap Steps, Outcomes, and Publications

Step	**Outcomes**	**Publications**
1. Identify concrete railway problems	Taxonomy of AI for railways, Identification of Railway problems, Review of AI applications to Railway problems, Identification of research directions and uncharted areas emerged from the analysis of the state-of-the-art.	D1.1, D1.2, [8,9,11–13].
2. Identify constraints, applicability issues, and requirements.	Review of EU guidelines, Regulations, and directives on AI, Explainable AI, Criticalities and milestones, Ethical and Privacy aspects, Urgent issues, and Strategic application areas.	D1.1, D1.3, [8].
3. Specify technology areas, pilot case studies, and operational scenarios.	AI Emerging Technologies in sectors other than Railways, Transferability guidelines, Pilot Case studies identification, Scenarios definition.	D2.1, D2.2, D3.1, D3.2, D4.1, D4.2.
4. Transform requirements into technology drivers.	Basic AI Usage Guidelines, Enabling Technologies, Reference datasets, and Machine Learning (ML) models.	D1.3, D2.1, D2.2, D3.1, D3.2, D4.1, D4.2, [4,6].
5. Develop AI-powered approaches, Identify alternatives, and their timelines.	PoCs for the selected scenarios: KPIs, ML models, Experiments, Results, and Possible alternatives.	D2.3, D3.3, D4.3, [5,10].
6. Identify innovation needs and recommended improvements.	Results of a SWOT* Analysis of the PoCs, Recommendations, and Innovation Needs.	D2.4, D3.4, D4.4
7. Create the Technology Roadmap Report	Timeline indications derived from i) previous steps, ii) relevant stakeholders' opinions, and iii) further available analysis results. Current criticalities and suggested research directions for innovation.	All the above, D5.3.

DX.Y stands for work package X deliverable Y.
References refer to scientific works published under RAILS agreement.
* SWOT: Strengths, Weaknesses, Opportunities and Threats [7]

Conceptual Shift. We identified Grades of Intelligence (GoIs), which, building upon the Grades of Automation (GoA), define a gradual integration of AI in autonomous trains [4]: i) *limited or no autonomy (GoI1)*, where AI is not adopted in safety-critical functionalities but can be used to optimize the use of resources;

ii) *partial autonomy (GoI2)*, where AI is used to improve train operation or train protection; iii) *full autonomy (GoI3)*, where AI is adopted to optimize both operations and protection, e.g., in Virtual Coupling [5]; iv) and *full autonomy in fully connected environments (GoI4)*, where advanced AI functionalities are added to GoI3 through dynamic learning and adaptation.

Structural Needs. To move towards *GoI4*, we defined Levels of Intelligence (LoIs) based on edge, fog, and cloud computing to provide a reference architecture for the distribution of AI functionalities (see Fig. 1).

Recommendations. RAILS recommendations have been mainly oriented towards i) the identification of approaches to manage the complexity of AI systems (i.e., explainable AI); ii) the strategies for data generation (e.g., simulators and 3D editors), standardization, and sharing; iii) the definition of ad-hoc regulations for the certification of AI systems; iv) the investigation of approaches integrating Digital Twins (DTs) and Mixed Reality to test and validate AI-based safety-critical systems.

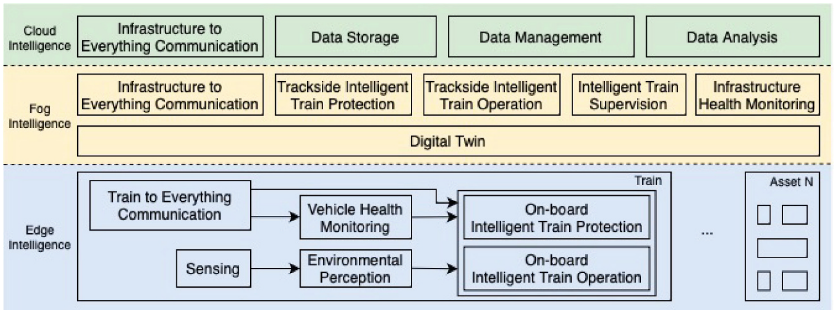

Fig. 1. Example Architecture for GoI4 Railway Lines.

4 Intelligent Infrastructure Inspection

AI is the main enabler for the paradigm shift from scheduled inspections to continuous monitoring and corrective to predictive maintenance. In RAILS, we identified the following main aspects supporting such a paradigm shift.

Non-intrusiveness. Railway components must comply with specific norms and regulations. In RAILS, we focused on the adoption of non-intrusive audio-video sensors, using artificial hearing and vision, to continuously monitor railway systems without interfering with train operations, and hence with no impact on compliance with reference standards.

AI-aided DTs. AI extends DTs allowing for the deployment of intelligent services such as predictive maintenance; also, it provides the capability of emulating the behavior of their physical counterpart. An example architecture for AI-aided

DT [6], including implementation guidelines. We showed that non-intrusive sensors combined with data processing based on AI can extract specific information that is crucial for the successful implementation of DTs.

Recommendations. Considering the aspects described above, the recommendations provided in RAILS mainly refer to the experimentation of non-intrusive monitoring, the investigation of possible solutions to integrate DTs, and the overcoming of some issues related to DT implementation (e.g., interoperability) and AI approaches (e.g., small-scale object detection and robustness to noise). In addition, data generation and collection to train and test AI models can also be critically sensitive; the same recommendations provided in Sect. 3 for data generation and collection also hold here, especially regarding deep transfer learning and domain adaptation.

5 Route Embedding for Arrival Delay Prediction on Service Basis

The Train Delay Prediction Problem has been investigated by a large number of studies. How to best represent certain features of a train is key to successful prediction. For instance, due to its complex topological nature, a train's route (i.e., origin, intermediate stations, and destination that a train service calls) is one of the most useful and essential features, but it is difficult to represent properly. Considering this, in RAILS we introduced graph embedding to identify the feasibility of its capability to understand and interpret the complex structure of a railway network including network topology, and train profile.

Network Topology. Incorporating both network spatial characteristics and historical delay information into a train delay prediction framework is a critical endeavor in enhancing the efficiency, reliability, and safety of modern railway systems. In addition to operational improvements, this integration also contributes to safety enhancements. By identifying and addressing vulnerable areas of the network, railway operators can proactively implement safety measures and reduce the risk of accidents occurrence.

Deep Network Embedding. A deep neural network-based graph embedding technique represents a cutting-edge approach for extracting rich and informative network features and enabling a wide array of applications across various domains by considering both the global and local aspects of networks. This methodology facilitates downstream machine learning tasks by providing a compact and expressive representation of nodes and edges within the network. As these techniques evolve, they are likely to play an increasingly crucial role in network analysis and data-driven decision-making.

Recommendations. Taking the aforementioned aspects into account, the recommendations identified in RAILS refer to the i) implementation of the Structural Deep Network Embedding approach, and then integrating it with dimension decomposition methods. To generate route embedding vectors as information entropy condensed features, contributing to the subsequent arrival delay prediction. ii) Transfer learning in railway networks, i.e., applying knowledge from one network to another, which is valuable when data is scarce or for newly built networks. iii) Ensemble methods in machine learning, combining multiple models to enhance prediction accuracy and reliability. Different models have strengths and weaknesses, but ensembles leverage their collective wisdom, particularly when models are diverse.

6 Conclusion

We believe RAILS has provided a significant contribution to shaping the future of AI and machine learning technologies in railways due to the critical analysis of the state-of-the-art, specific taxonomy development, and case-study experimentation in selected areas. Furthermore, to better define the roadmaps towards effective AI adoption in railways, we also shared project results with worldwide railway experts from academy and industry. That allowed us to identify the current state of development of intelligent technologies in terms of their Technology Readiness Level (TRL). During project workshops, we collected experts' opinions on when specific AI technologies will achieve full maturity to be used in railway environments, and which will be the main criticalities to overcome.

Therefore, we expect that RAILS project results will have a significant impact due to the provision of essential guidelines and recommendations, as well as promising future directions for the successful adoption of AI and machine learning in next-generation smart railways.

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