# WP2: AI for Rail Safety and Automation Cooperative Driving for Virtual Coupling of Autonomous Trains

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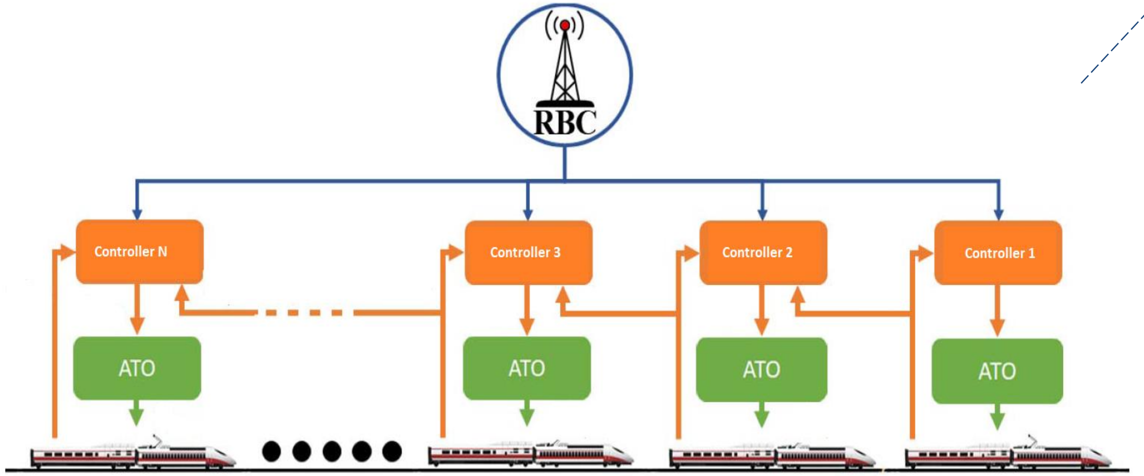
# Railway Problem and Motivation




**Objective of the PoC**
Exploring the feasibility
of Railway Virtual Coupling
through AI techniques

**Constraints / Requirements**
Optimizing the inter-train distances
while preserving safe operations

**Main Issues and Challenges**
Need of ad-hoc simulators

**Key Performance Indicators (KPIs)**
Tracking index
Energy consumption

# Proof-of-Concept as a Benchmark

**AI Application**
Cooperative and Autonomous Driving

**AI Techniques**
Deep Reinforcement Learning
Deep Deterministic Policy Gradient

**Inspiring Solutions**
Platooning in Automotive

**Developments / Implementations**
Virtual Coupling Control Strategy
Ad-hoc Simulation Platform

**Exploited Software and Framework**
Matlab/Simulink
Keras, Tensorflow, OpenAiGym

**Testing and Validation**
Definition of Operational Scenarios and Manoeuvres

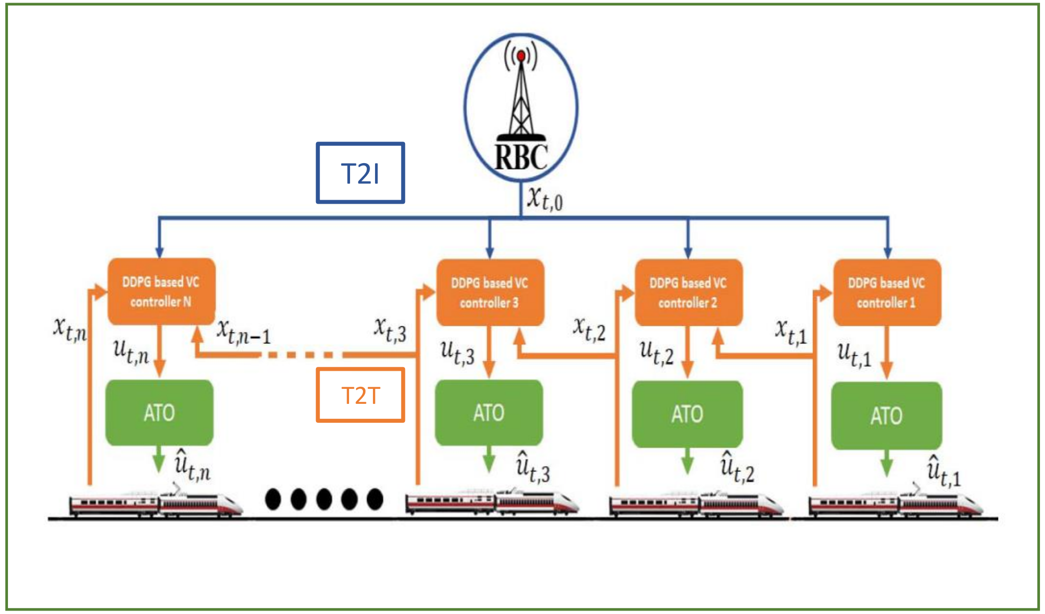
**Assessment**
Comparison with a traditional approach

# Virtual Coupling (VC) for High-Speed Trains: Problem Description

- We consider a convoy of heterogeneous autonomous High-Speed Trains plus the Radio Block Center (RBC) which, acting as the virtual leader, imposes the reference behavior for the overall autonomous convoy through a T2I communication network.

- Each train, equipped with an on-board T2T communication device, can share its state information, i.e., absolute position and speed, with the other communicating trains.

- Within this context, the aim is to ensure that each train travels at the desired speed imposed by the virtual leader while maintaining, in different cooperative driving scenarios, a secure inter-train distance which explicitly considers the relative braking curves.



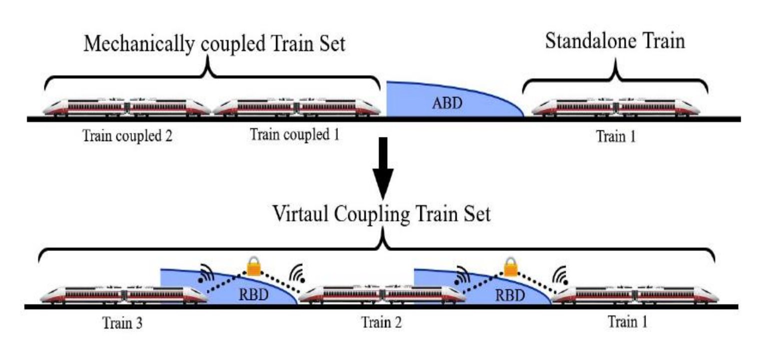

Virtual Coupling Conceptual Architecture

# Problem Statement

Consider a convoy of heterogeneous connected autonomous High-Speed Trains plus the virtual leader. Find a robust decentralized **VC Control Strategy** driving the motion of each train in tracking the reference behavior while maintaining the safe inter-train distance w.r.t. its predecessor, despite the presence of:

- uncertainties in train dynamic parameters;
- heterogeneity in trains’ dynamics, which are characterized by different operational performances (e.g., different braking capabilities, different speed categories);
- uncertainties in track conditions (e.g., adhesion factors and gradients profile), external disturbance (e.g., wind speed) and unknown exogenous forces due to the curvature and the slope;
- uncertainties in reaction delay when performing braking maneuvers, which influence the inter-train distance;
- uncertainties in train location information;
- on-board speed error measurements for each train.

**System Requirements for Safety Braking Distance**: Since one of the VC goals is to increase the line capability by replacing the traditional Absolute Braking Distance with a Relative Braking Distance, an accurate definition of the safe inter-train distance is provided for each train, which takes into account the most favorable braking condition for the preceding train and the guaranteed emergency brake rate for the considered train. In addition, it explicitly considers the braking reaction delay, the time required for its computation, the maximum and minimum acceleration rate, as well as uncertainties in train location information.

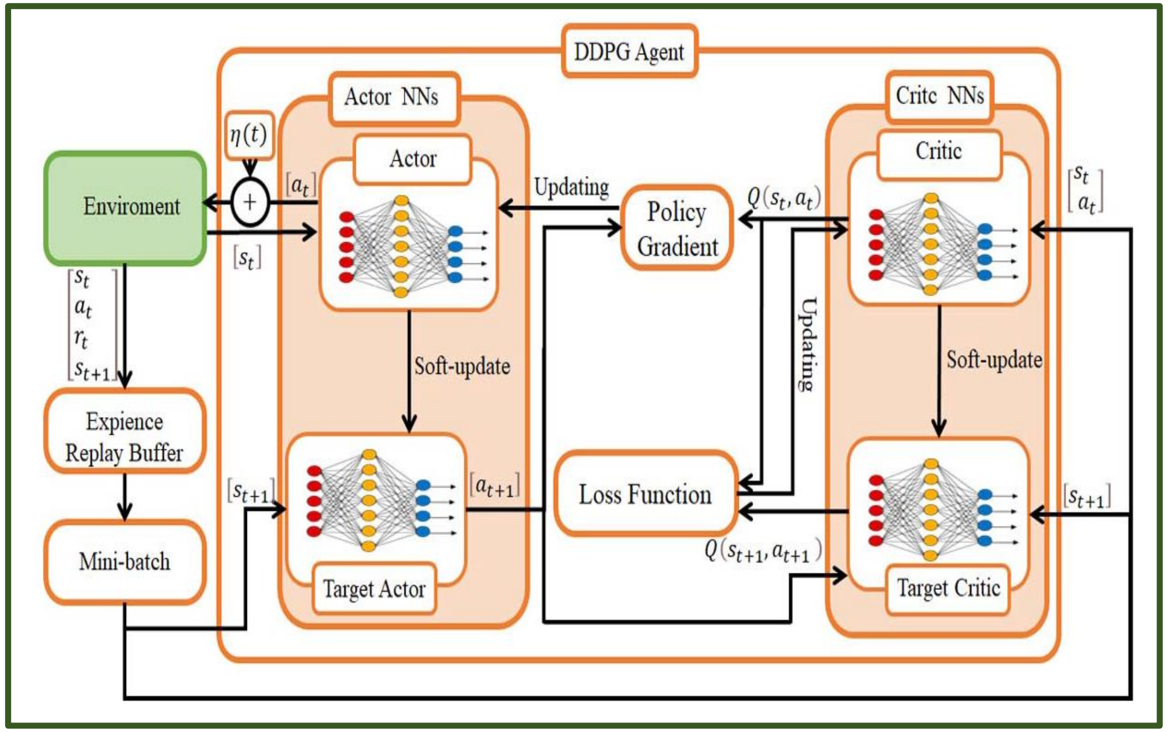



From Absolute to Relative Braking Distance [1]

[1] Schenker, M. (2020). S2R Innovation Days Presentation X2R3-TD2. 8 Virtually Coupled Train Sets.

# Deep Deterministic Policy Gradient (DDPG) VC Controller

- To solve the VC control problem, a novel decentralized **DDPG-based control architecture** has been proposed, where each train is equipped with a DDPG agent which computes the control action to be imposed according to the environmental reactions, the information shared by the predecessor train and the leader.
- Each DDPG agent is composed of **4 fully-connected Deep Neural Networks (DNN)**, i.e., actor, actor target, critic and critic target: actors compute the action to be performed by each train, while the critics evaluate the quality of the chosen action according to a **learning-by-doing** process.
- For each agent, a **reward function** is defined according to the VC control requirements.
- At each time instant, the DDPG agent, interacting with the environment and based on the past and present observations state, computes and performs the chosen action, receiving a new state and a reward.
- The **control input** is hence computed at each step with the aim of maximizing the **cumulative reward function**.

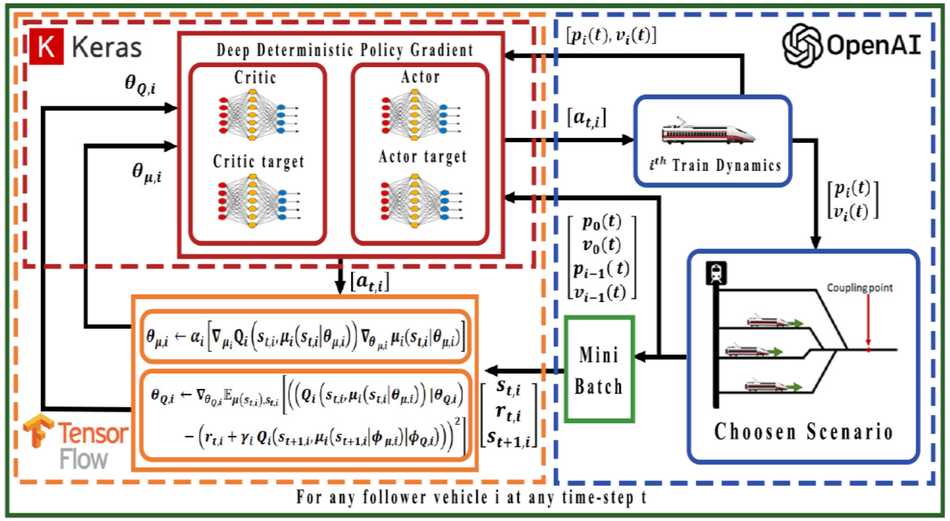



Control architecture of the DDPG agent for the computation of the control action

# VC Simulation Platform for Training and Validation

We designed an ad-hoc Simulation Platform which allows to emulate:

- heterogeneous trains dynamics;
- different operating driving conditions and train heterogeneity;
- T2T and T2I communication networks;
- the strategic layer logic for the emulation of the coupling/decoupling commands;
- different railway environments and operational scenarios;
- adhesion factors for different weather conditions;
- curvature radii and gradient profiles;
- windy conditions.




Proposed Simulation Platform

The proposed simulator has been exploited for both the training and validation phases of the proposed DDPG controller.

<u>**Training**</u>: The effectiveness of the training results in terms of average and cumulative reward function confirmed that the DDPG agent has *learned* the correct behavior to be imposed to the train *by doing*.

<u>**Validation**</u>: The capability of the developed control architecture in guaranteeing the VC for the convoy has been assessed considering different operational scenarios involving the following cooperative maneuvers:
**Convoy Forming, Convoy Splitting, Leader-Tracking**.
Results showed the effectiveness and the robustness of the proposed control strategy in ensuring the considered maneuvers while maintaining a safe inter-train distance.

# Comparison Analysis

The performance of the proposed DDPG controller has been compared with the one achievable via the Model Predictive Control protocol proposed in [2] through two suitable KPIs:

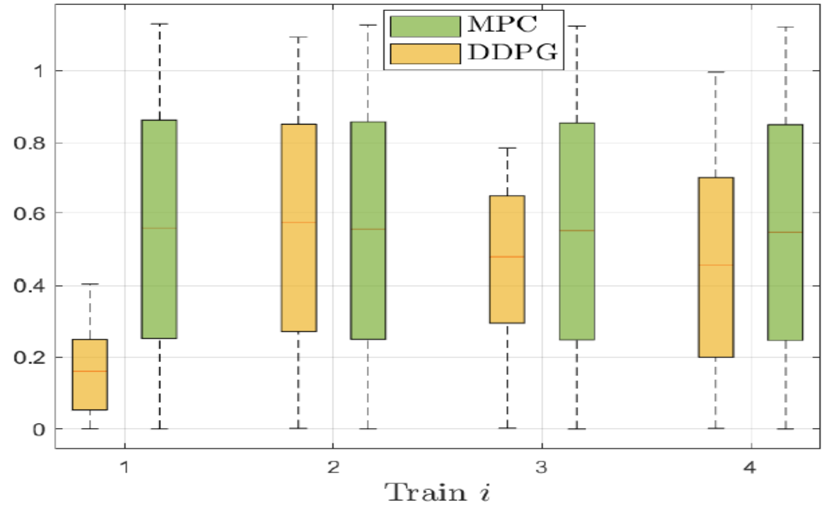
- **<u>Tracking Index</u>:** it evaluates the effectiveness of the controller in tracking the reference behavior imposed by the virtual leader;
- **<u>Energy Consumption</u>:** it assesses the energy saving ensured by the control actions.

Figures show the two KPIs computed for each train of the convoy and confirm:

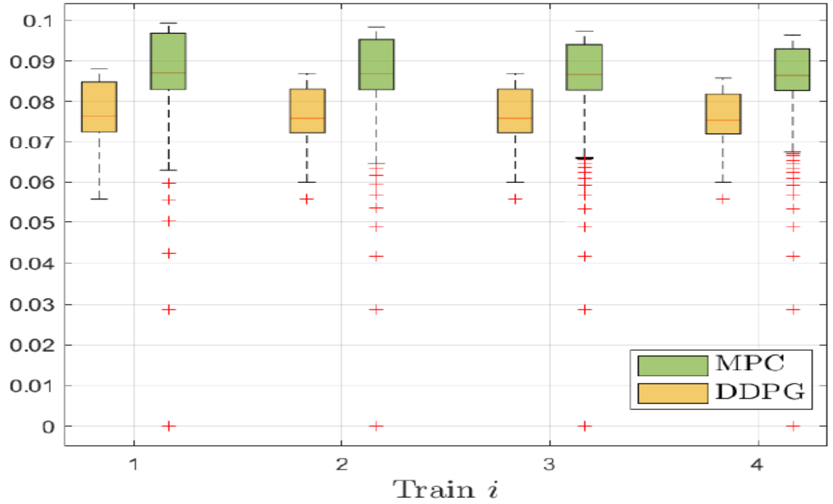
- the improvement in **tracking** and **robustness** performance achievable via the proposed DDPG-based approach, since it is less sensitive to parameter uncertainties, differently from MPC;
- the improvement in **energy saving**.

A better reference tracking guarantees an **increasing in lane capacity**, which is one of the main goals of VC.

**KPI 1: Tracking Index**




**KPI 2: Energy Consumption [KWh/km]**

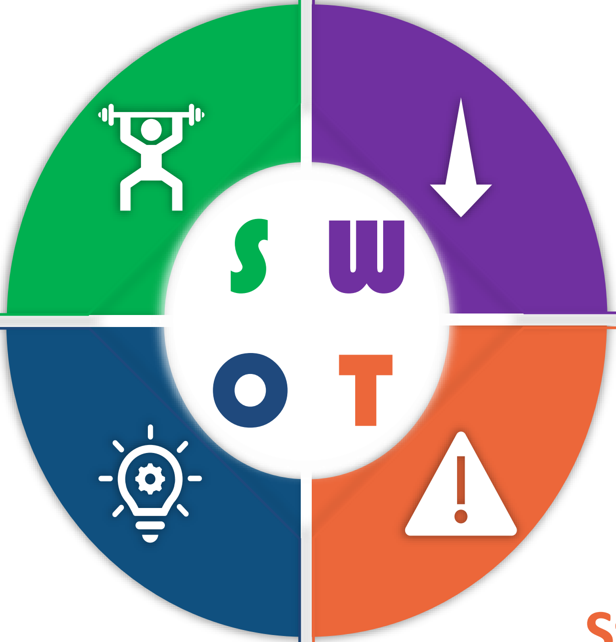



[2] Su, S., She, J., Li, K., Wang, X., Zhou, Y., 2021. A nonlinear safety equilibrium spacing based model predictive control for virtually coupled train set over gradient terrains. IEEE Transactions on Transportation Electrification.

# SWOT Analysis of the Investigated Approach

Increase in lane capacity
Energy saving
Flexibility
Robustness
PoC as benchmark

Validation of both tactical and operational layers
Computational time




Advanced simulators
T2X communication technologies
Explainable RL

Explainability
Standards and regulations

# Recommendations

Development of advanced Railway Simulators for Virtual Testing

Validation of the entire Virtual Coupling Architecture

Exploring the potential of Explainable Reinforcement Learning for VC applications

Extension of the current Railway Standards and Regulations to AI applications

# Thank you for your attention!

RAILS Roadmaps for AI Integration in raiL Sector

- ✓ *Deliverable D2.1: WP2 Report on case studies and analysis of transferability from other sectors (safety and automation)*
- ✓ *Deliverable D2.2: WP2 Report on AI approaches and models*
- *Deliverable D2.3: WP2 Report on experimentation, analysis, and discussion of results*
- *Deliverable D2.4: WP2 Report on identification of future innovation needs and recommendations for improvements*

*Available at: https://rails-project.eu/downloads/deliverables/*