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Functional Modeling of Autonomous Train Operation (ATO) Systems

Florianópolis
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Functional Modeling of Autonomous Train Operation (ATO) Systems

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This work is dedicated to my family,
especially my parents and my sister.
It is also dedicated to the friends I've met along the way.

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« L'important dans la vie, ce n'est point le triomphe, mais le combat ;
l'essentiel n'est pas d'avoir vaincu, mais de s'être bien battu.»
(COUBERTIN, 1908)

DISCLAIMER

Le Mans, February 23rd, 2026.

As representative of the SNCF Voyageurs, in which the present work was carried out, I declare this document to be exempt from any confidential or sensitive content regarding intellectual property, that may keep it from being published by the Federal University of Santa Catarina (UFSC) to the general public, including its online availability in the Institutional Repository of the University Library (BU). Furthermore, I attest knowledge of the obligation by the author, as a student of UFSC, to deposit this document in the said Institutional Repository, for being it a Final Program Dissertation (*"Trabalho de Conclusão de Curso"*), in accordance with the *Resolução Normativa n°126/2019/CUn*.



Matthieu Thibault
SNCF Voyageurs

ABSTRACT

The work addresses the problem of limited capacity and operational instability on high-speed railway corridors, motivated by the need to increase the number of trains per hour on the Paris–Lyon line without compromising safety, regularity, or energy efficiency under the European Railway Traffic Management System (ERTMS) Level 2 standards. It proposes the use of Automatic Train Operation (ATO) at Grade of Automation 2 as a technological solution to reduce variability in driving behavior, mitigate the so-called "accordion effect," and enable shorter headways between trains. To investigate this potential, the study develops a functional and modular simulation model of train circulation that represents the interaction between trains, infrastructure, and signaling systems. The implementation relies on MATLAB/Simulink and integrates detailed train dynamics, supervision logic through the European Vital Computer, traffic management by a Radio Block Center, and two modes of operation: manual driving based on behavioral models calibrated with real operational data, and automated driving based on both an ideal reference controller and a Model Predictive Control strategy. The methodology follows a data-driven, scenario-based approach that iteratively refines the models and evaluates performance under different traffic conditions, departure intervals, and disturbance levels, using metrics such as timetable adherence, headway stability, and capacity potential. The results demonstrate that ATO can improve operational regularity, reduce unnecessary braking and acceleration cycles, and allow a reduction in departure intervals while maintaining safety margins, thereby increasing effective line capacity. The study delivers a quantitative and reproducible framework that supports decision-making on ATO deployment, providing value to railway operators and infrastructure managers by clarifying expected gains, limitations, and conditions for successful implementation.

Keywords: Automatic Train Operation; ERTMS Level 2; high-speed railways; MATLAB/Simulink; railway capacity; Model Predictive Control.

RESUMO

O trabalho aborda o problema da limitação de capacidade e da instabilidade operacional em corredores ferroviários de alta velocidade, motivado pela necessidade de aumentar o número de trens por hora na linha Paris–Lyon sem comprometer a segurança, a regularidade ou a eficiência energética sob os padrões do Sistema Europeu de Gestão do Tráfego Ferroviário (ERTMS) Nível 2. Propõe-se a utilização da Operação Automática de Trens (ATO) no Grau de Automação 2 como solução tecnológica para reduzir a variabilidade no comportamento de condução, mitigar o chamado “efeito sanfona” e permitir menores intervalos de separação (headways) entre trens. Para investigar esse potencial, o estudo desenvolve um modelo de simulação funcional e modular da circulação de trens que representa a interação entre trens, infraestrutura e sistemas de sinalização. A implementação baseia-se em MATLAB/Simulink e integra dinâmica detalhada do trem, lógica de supervisão por meio do Computador Vital Europeu (EVC), gestão de tráfego por um Centro de Bloqueio por Rádio (RBC) e dois modos de operação: condução manual baseada em modelos comportamentais calibrados com dados operacionais reais e condução automatizada baseada tanto em um controlador de referência ideal quanto em uma estratégia de Controle Preditivo por Modelo (MPC). A metodologia segue uma abordagem orientada por dados e baseada em cenários, refinando iterativamente os modelos e avaliando o desempenho sob diferentes condições de tráfego, intervalos de partida e níveis de perturbação, utilizando métricas como aderência ao horário, estabilidade dos intervalos entre trens e potencial de capacidade. Os resultados demonstram que o ATO pode melhorar a regularidade operacional, reduzir ciclos desnecessários de frenagem e aceleração e permitir a redução dos intervalos de partida, mantendo as margens de segurança e, assim, aumentando a capacidade efetiva da linha. O estudo apresenta uma estrutura quantitativa e reprodutível que apoia a tomada de decisão sobre a implantação do ATO, oferecendo valor a operadores ferroviários e gestores de infraestrutura ao esclarecer ganhos esperados, limitações e condições para uma implementação bem-sucedida.

Palavras-chave: Operação Automática de Trens; ERTMS Nível 2; ferrovias de alta velocidade; MATLAB/Simulink; capacidade ferroviária; Controle Preditivo por Modelo

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1 INTRODUCTION

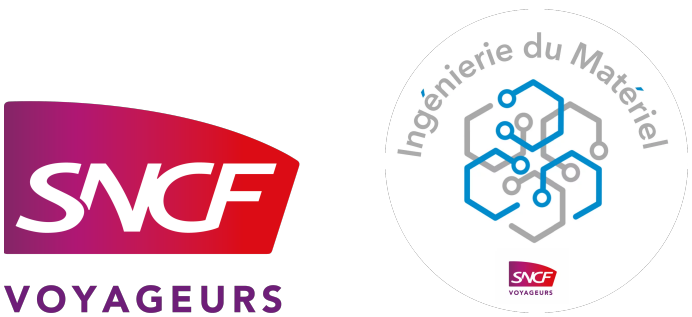
In the context of high-speed railway networks, especially in France, there is an increasing demand for services, since trains are becoming the preferred option for passengers seeking speed and convenience with a reduced environmental impact in comparison to other means of transportation, such as airplanes (Givoni, 2007).

In recent years, France has witnessed a significant surge in high-speed rail demand, particularly on the *Trains à Grande Vitesse* (TGVs) - the high-speed trains. In 2024, over 126 million passengers were transported on the TGV INOUI services, marking a 3.5% increase from the previous year (SNCF Voyageurs, 2024). In addition to that, railway services in France have recently been opened up to external competition, allowing companies other than SNCF to participate in the market.

This increase in demand, along with the market changes, forces the railway operating companies, such as the SNCF *(Société Nationale des Chemins de fer Français)*, to invest in research to find ways to accommodate these new passengers on the existing network. The integration of technology is one of the major keys to improving not only the capacity, but also other aspects like the quality of the service and energy efficiency. Moreover, keeping up with innovation allows the company to strengthen its reputation in the transportation sector, positioning itself as a reference for excellence, innovation, and reliability in railway transportation, setting standards for others to follow in both national and international markets.

The evolution of railway systems worldwide has been driven by the need to meet these growing mobility demands while simultaneously improving operational efficiency and sustainability. Innovations in automation technologies are playing a very important role in transforming traditional railways into more adaptive networks. *Autonomous Train Operation* (ATO) systems represent a significant advancement in this direction, offering potential benefits such as increased service frequency, improved punctuality, and optimized energy consumption.

Figure 1 – Official logos of the *SNCF Voyageurs* and its *Centre d'Ingénierie du Matériel* (CIM)

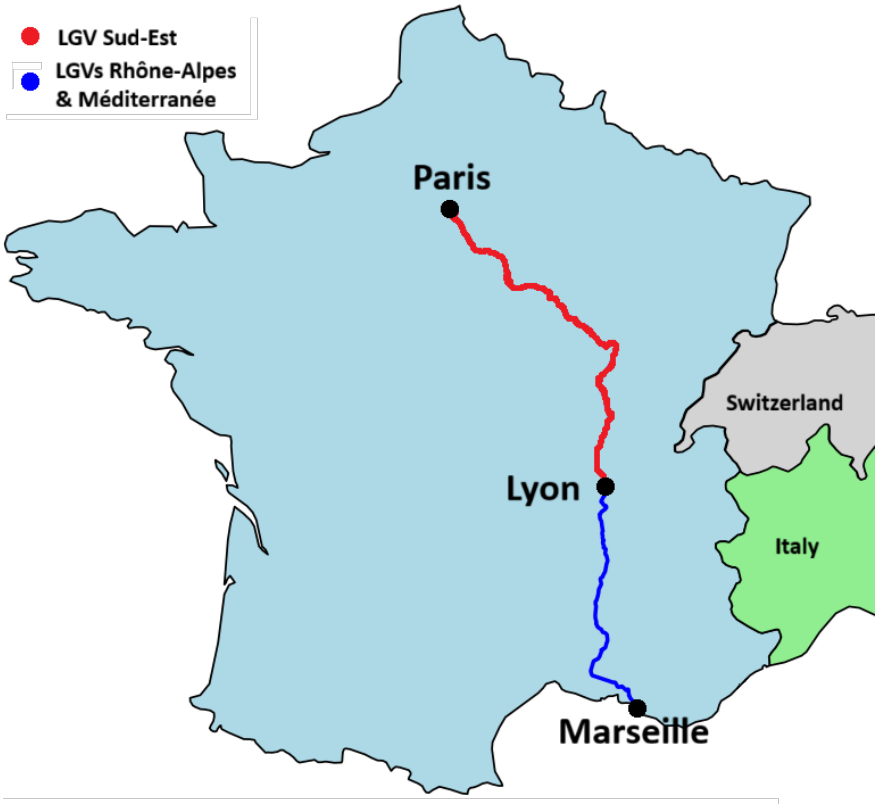


In this context, the present work was developed at the *Centre d'Ingénierie du Matériel* (CIM) of SNCF, the "Railway Equipment Engineering Center", located in Le

Mans, France. The CIM is responsible for the engineering and research to propose improvements to the railway equipment used all around the French territory, across the SNCF network. The project presented here is among SNCF's research efforts on the development and validation of ATO systems, proposed as an operational improvement aimed at efficiency, reliability, and safety of train services.

The background for this project is the Paris–Lyon line, one of the busiest train lines in Europe, with over 45 million passengers per year (Voyager en train, 2022). This line corresponds to the *LGV Sud-Est* high-speed railway, a 409 km railway that connects Paris and Lyon directly. This railway is operated alongside the *LGV Rhône-Alpes* and the *LGV Méditerranée*, resulting in the *Ligne de Combs-la-Ville à Saint-Louis*, a 711 km railway that allows fast commuting between the three largest cities in France - Paris, Marseille and Lyon - as well as access to other railways to nearby countries such as Switzerland and Italy.

Figure 2 – Detailed map of the *Ligne de Combs-la-Ville à Saint-Louis* high-speed railway, highlighting the section Paris-Lyon



The main problem this project aims to address is the limitation of capacity in high-speed rail corridors, such as Paris-Lyon. Currently, this line operates with trains spaced by a minimum of approximately four and a half minutes, resulting in a maximum capacity of 13 trains per hour (SNCF Réseau, 2024). This time between trains is the result of the enforcement of safety measures from the European Railway Administration (ERA), that take into consideration several variables that guarantee the safety of the

operations, such as the braking capacities of the trains, the transmission delays on the messages exchanged between the onboard systems and the trackside equipment, the reaction time of the human operator, etc.

Reducing this headway, while maintaining safety and operational robustness, could significantly increase capacity without requiring new infrastructure. However, when train intervals become shorter, undesirable effects such as the so-called “accordion effect” may arise — when repeated cycles of braking and acceleration lead to instability, higher energy consumption, and potential delays, along with a back-propagation of abrupt braking or other sudden maneuvers. Modeling and understanding these dynamics is essential to developing automation strategies capable of improving performance and stability under such conditions, and also for determining the expected gains when transitioning from manual driving to ATO. The goal of the company is to achieve a capacity of 16 trains/hour in peak hours on this line, by investing in technology and innovation to integrate into the European-standard ERTMS signalling system. (SNCF Réseau, 2024)

In this context, ATO emerges as a promising solution to achieve the desired performance and improve the regularity of operations. By reducing variability between operators and enabling more consistent responses to speed limits, braking profiles, and timing constraints, ATO has the potential to enhance the overall capacity of the line. However, its actual ability to reach the targeted performance levels still needs to be evaluated. A detailed assessment is required to determine whether the introduction of ATO will indeed deliver the expected capacity gains compared to manual driving, or whether additional measures will be necessary to meet the operational objectives.

1.1 Objectives

The project’s overall objective is to evaluate how ATO can improve railway operations compared to manual driving, with a specific focus on capacity enhancement and the system’s reaction to operational perturbations, under the European standards and norms established by the European Rail Traffic Management System (ERTMS) Level 2.

To achieve this goal, the specific objectives are:

1. Developing a functional simulation model of train circulation in a parametrizable high-speed line, modeling the dynamics of several trains running on a line and considering the interaction between several trains, parameters such as traction and ETCS braking curves, and disturbances such as gradient effects (slopes and descents);

2. Implementing both manual (based on real train data) and automatic (ATO) operation modes by modeling different operational profiles, and assessing the gains and significant changes resulting from the ATO implementation;

3. Simulating different scenarios to assess metrics such as stability, and timetable adherence for both manual and automatic operations.

1.2 Approach and Methodology Overview

The proposed approach is based on the creation of a simulation model in MATLAB/Simulink, reproducing a train line and each of the trains on it, modeling the interaction between the trains, the track, and the supervision system. The initial model architecture includes a command center, the Radio Block Center (RBC), responsible for communicating and managing movement authorizations for each train, along with multiple instances of a train model, equipped with subsystems such as the onboard computer (European Vital Computer/EVC), the operator model, and the train dynamics model. Initially, the system reproduces manual driving (Grade of Automation 1 – GoA1) using empirical data and behavioral modeling of the human operator. Subsequently, automation functionalities (GoA2) are implemented to simulate ATO-controlled driving, enabling direct comparison between manual and automatic modes.

The development methodology combines literature review, system modeling, simulation, and optimization. In the first phase, the study focused on understanding railway signaling systems, operational procedures, and the ATO architecture, alongside a review of existing research on automatic train control and an identification of the current state of the Paris-Lyon railway. The following phases concentrated on model implementation and validation, based on real-world data from the Paris–Lyon high-speed line. The subsequent phases involve integrating ATO functionalities and evaluating performance improvements in different metrics, such as headway stability, disturbance recovery, and energy consumption.

By providing quantified metrics to assess the potential benefits of ATO adoption, this study is relevant for the field of railway automation and for the host institution, contributing to the technological advancements in this field. Academically, it applies principles of control and automation engineering — such as dynamic system modeling, control, and optimization — to a complex real-world system, putting together theoretical concepts with their practical application.

1.3 Document Organization

The present document is organized as follows: Chapter 2 presents the theoretical foundation of the project, covering the main concepts of railway signaling, ERTMS architecture, train dynamics, and ATO principles. Chapter 3 describes the problem in detail, outlining the operational constraints, modeling requirements, and available data sources, while Chapter 4 introduces the proposed modeling approach and methodology. Chapter 5 presents the development results, the models and simulations made during

the internship, and a performance analysis under different operational scenarios. Finally, Chapter 6 summarizes the main conclusions of this work and proposes directions for future studies and developments.

2 THEORETICAL FOUNDATION

This chapter presents an overview of the key concepts of the project, explained within technical context. Section 2.1 explains important concepts on railway systems, such as signaling, braking curves and the ERTMS system. Section 2.2 explains how the train dynamics are represented in this study, while Section 2.3 explains the specifics of the Automatic Train Operation (ATO), and presents the aspects behind an ATO implementation with predictive control.

2.1 Overview of Important Railway Operation Concepts

Railway operation is built upon a complex framework of standards, norms, and technical systems. These structures ensure safety, interoperability, and consistency across different rolling stock and infrastructure, while allowing for efficient operations. In Europe, the European Union Agency for Railways (ERA) is making an effort to unify the protection and signaling across different countries. Fig. 3 shows that each country has historically implemented its own operational railway systems, meaning that to circulate across national borders, several different onboard systems were needed. This justifies as well ERA's effort to develop of a unified system, the European Railway Traffic Management System - the ERTMS.

In this context, one of the most important concepts to be discussed is the role of signaling. Signaling systems are responsible for translating infrastructure constraints, traffic conditions, and safety requirements into clear operational limits for the train, ensuring safe separation between movements and enabling efficient traffic management. Modern signaling — particularly under ERTMS — integrates continuous speed supervision, braking-curve calculation, and communication-based updates to movement authority, representing a shift from fixed, trackside information to dynamic, on-board intelligence. For high-speed lines, at speeds above 250–300 km/h, visual detection and interpretation of fixed signals become impractical and unsafe, given the limited reaction time available to the driver. For this reason, operations rely primarily on onboard signaling, where all relevant information — such as speed limits, movement authorities, and braking-curve supervision — is transmitted and displayed directly on the Driver Machine Interface (DMI), through the regulation systems.

A key element within this onboard supervision is the computation of braking curves, which play a crucial role in ensuring safe and efficient train operation. Braking curves describe the precise deceleration profile that a train must follow in order to reduce speed or stop before reaching a critical point on the track, such as a speed restriction, a signal at danger, or the end of its movement authority. They are calculated continuously by the onboard unit based on train-specific data — including mass, braking performance, gradient, and adhesion conditions — together with the limits imposed by

Figure 3 – Different train protection systems used in each European country (Simoni, 2025a)



the signaling system. By defining the latest safe point at which the train must begin braking and supervising the driver's adherence to this profile, braking curves provide a dynamic safety envelope that prevents overruns and optimizes the use of available track capacity. Thus, they constitute one of the fundamental mechanisms through which modern signaling systems translate operational constraints into real-time, enforceable safety margins. The calculation of braking curves in ERTMS is performed by the European Train Control System - ETCS, which is one of the key components of the management system.

2.1.1 The ERTMS/ETCS system

The European Rail Traffic Management System (ERTMS) is the unified signalling and train control framework developed to enhance interoperability, safety, and efficiency across European rail networks. Its core component, the European Train Control System (ETCS), replaces the different Automatic Train Protection (ATP) systems proposed by each country, with a standardized architecture capable of supervising train movements. ETCS introduces a common set of rules, interfaces, and data structures that allow trains equipped with the onboard system to operate across borders, independent of the national infrastructure on which they run.

In the context of specifications and implementation of the ERTMS/ETCS, lies the ERA Subset series. There are different subsets that provide the functional and logical foundations of the system, including definitions of movement authority handling, speed profiles, target speeds, braking curves, onboard supervision rules, and the communication protocols with trackside components. In this study, Subset-026 (European Union Agency for Railways (ERA), 2016) is the most important document, since it describes precisely how the onboard unit receives, processes, and reacts to information from the Eurobalises - trackside devices that send data to the train - and from the Radio Block Centres (RBCs), including speed restrictions, gradients, and other infrastructure data.

From an operational perspective, ETCS works by continuously calculating the permitted speed and distance available to the train based on the movement authority issued by the trackside system. Under ETCS Level 2, movement authorities and updates are sent continuously via radio communication from the RBC, enabling real-time supervision without reliance on trackside signals. Higher levels (such as Level 3) introduce moving block principles, further optimizing capacity by dynamically adjusting safe separation distances. The context of this work is a Level 2 implementation.

Figure 4 – Communicating devices in ERTMS/ETCS Level 2 (Simoni, 2025c)



Within the onboard system, the ETCS processes inputs — including train characteristics, gradient profiles, permitted speeds, temporary speed restrictions, and infrastructure data — and computes the relevant supervision limits. This includes the calculation of braking curves, target speeds, warning distances, and service versus emergency intervention thresholds. These calculations ensure that the train remains within a "safe envelope" at all times, automatically triggering service or emergency braking if the driver fails to comply with the permitted speed profile. The resulting information is presented to the driver through the Driver–Machine Interface (DMI), providing clear guidance on current speed, target speed, distance to target, and any upcoming operational constraints.

Overall, the ERTMS/ETCS system represents a shift from fixed, trackside-based signalling to a dynamic, interoperable, and onboard-intelligent system. Its standardization enables higher safety integrity, better capacity usage, improved high-speed operation, and cross-border interoperability — fully aligned with the long-term objectives of the European Union Agency for Railways (ERA).

Calculation of Braking Curves

A key concept in train supervision under ETCS is the calculation of different braking curves, including the Emergency Brake Deceleration (EBD) curve, which defines the maximum speed the train can have at each point along the track while still being able to stop within the movement authority limits. According to ERA Subset-026 (European Union Agency for Railways (ERA), 2016), the EBD curve represents a position-dependent deceleration profile that guarantees safe braking even under adverse conditions.

The calculation of the EBD curve relies on two main components:

1. **Train braking capability:** the maximum deceleration the train can achieve, which is speed-dependent and corrected by coefficients that account for adhesion conditions, brake type, and train-specific parameters such as mass and length. Variations in rail conditions, such as wet or dry rails, can modify the effective braking capacity.

2. **Track gradient:** the inclination of the track at each position along the route. Uphill gradients reduce the required braking effort, while downhill gradients increase it. Formally, the effective deceleration along the track can be expressed as

$$a_{\text{effective}}(x, v) = a_{\text{brake}}(v) \pm g \sin(\alpha(x)),$$

where $a_{\text{brake}}(v)$ is the train's maximum braking capacity at speed v, g is the gravitational acceleration, and $\alpha(x)$ is the track gradient angle at position x.

The EBD curve is thus a combination of these two effects, forming a dynamic safety envelope along the track. Subset-026 allows the calculation to be simplified by considering both the braking capability and the gradient effect as piecewise constant along a grid, dividing the track into discrete cells where the effective deceleration is assumed constant. The backward integration of these decelerations from the target point defines the latest safe braking points at each position.

This theoretical framework is essential to understand the calculations performed in the onboard system, the European Vital Computer (EVC), presented in Chapter 5. There, the EBD curve is computed in real time, taking into account both the train's braking characteristics and the position-dependent track gradient, forming the basis for supervised speed limits displayed to the driver.

Supervision Limits and Permitted Speed Calculation

Once the EBD curve has been computed, defining the latest possible braking points that still ensure a safe stop before the target, the onboard supervision system must derive from it the speed limits that effectively act on the train during operation. In the context of this work, and consistently with the braking-to-target framework of Subset-026 (European Union Agency for Railways (ERA), 2016), only the Emergency Brake Intervention (EBI) limit is considered.

The EBI curve is obtained by shifting the EBD curve backwards along the distance axis to account for the system reaction time. In Subset-026 terminology, this results in an intervention offset $\Delta x_{\text{reaction}}$, which ensures that, if the emergency brake has to be applied at the EBI curve, the effective deceleration will still respect the EBD envelope.

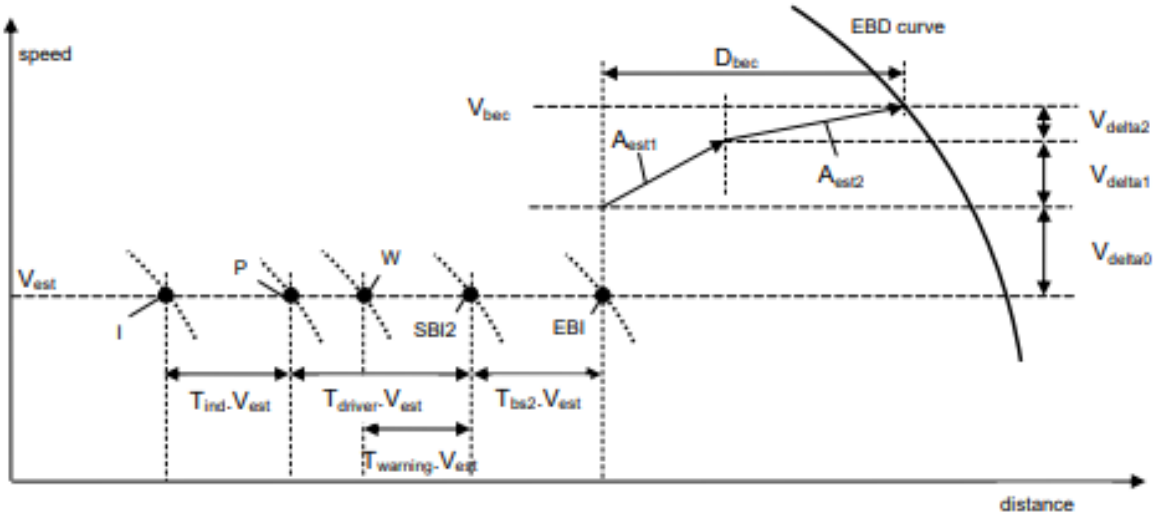
For each position x, the EBI curve is therefore defined as:

$$v_{\text{EBI}}(x) = v_{\text{EBD}}(x + \Delta x_{\text{reaction}}),$$

with the braking and gradient parameters evaluated at the shifted position. As shown conceptually in Fig. 5, extracted from Subset-026, the EBI curve lies above the EBD curve, providing an additional safety margin that compensates for the reaction delay.

From the EBI, always represented in a speed–position diagram, the emergency braking intervention point is obtained by intersecting the EBI curve with a horizontal line that represents the estimated actual speed, in the figure 5 denoted as V_{est}. This point denotes the exact position at which the train would automatically trigger its emergency braking if it continued running at this speed. Beyond this point, if no action is taken, the train would violate the EBI limit and trigger an emergency brake intervention. Thus, the indication point marks the latest position at which braking must begin to avoid an overspeed alert or intervention.

Figure 5 – Example from Subset-026 (European Union Agency for Railways (ERA), 2016) of the calculation of the supervision limits



The other important reference points, represented as I, P and W, are respectively the Indication, Permitted speed and Warning points. All three are calculated from the EBI intersection point with the current speed, by anticipating the intervention by a certain distance. This distance is calculated taking into consideration several different parameters of time, multiplied by the current speed to obtain a distance. First, the brake system delay T_{bs} is applied, that approximates the reaction time of the braking system when receiving a command from the operator and the actual braking. After that, $T_{warning}$ represents the delay of the last warning message before intervention, T_{driver} represents the reaction time of the operator, and T_{ind} represents the anticipation of the speed limit, representing the moment where a the permitted speed is shown to the operator on the DMI screen.

To summarize, the logic sequence of events is as follows: the operator keeps the train circulating at a speed V_{est}. Upon arriving at the intervention point (I), the permitted speed is shown on the screen, and the driver has a certain time interval T_{ind} to acknowledge this message. After that, if it keeps the same speed, it will arrive at the permitted speed/overspeed point(P). If the train crosses this point, it means that it has a higher speed than the one shown on the DMI screen, and the driver has not reduced it fast enough during the indication period. At this moment, the on-board computer will clearly state that the operation is in overspeed. After a brief delay, the warning point(W) arrives, triggering an alert that emergency braking will occur imminently. If after all these phases the speed is still not respecting the limits, the emergency brakes take action automatically at the EBI point and stop the train. It is important to say that these calculations are dynamic and the position of the points is a function of the speed - meaning that changing the speed between two points will displace them all and possibly change the current state.

In the framework of Subset-026, these indication points and supervision limits are therefore a direct geometric consequence of how the braking curves are constructed, from the EBD braking capability. When integrating an Automatic Train Operation (ATO) system, this relationship becomes even more relevant, by reducing the effective reaction times and bringing the supervision limits closer to the EBD curve, then moving the indication point downstream. This allows the train to maintain higher speeds for longer before braking, improving overall traffic performance. The impact of this effect is analyzed in the following sections.

2.2 Train Dynamics Modeling

The longitudinal dynamics of a train can be described, with sufficient accuracy for this study, using a simplified three-force model. This formulation captures the physical aspects of the train's acceleration and deceleration, while maintaining low computational complexity. A factor that greatly simplifies this modeling is the fact that the train moves exclusively on rails, which allows the motion to be considered essentially one-dimensional.

In this 3-forces model, the motion results from the balance of the following forces:

1. **Traction/Braking Force** (F_m): the controllable force generated by the propulsion or braking systems. It is positive during traction and negative during braking. Its value depends on the train's traction characteristics, on braking capability, and on the control input from the driver or automatic system.

2. **Movement Resistance** (F_{res}): a resistive force that always opposes motion. It is typically approximated by the Davis equation,

$$F_{\text{res}}(v) = A + Bv + Cv^2,$$

   representing rolling resistance (A), mechanical losses (Bv), and aerodynamic drag (Cv^2). This second-order polynomial provides a widely adopted approximation for mainline operations. The coefficients were obtained from previous studies conducted by the company,

3. **Gradient Force** (F_g): resulting from the inclination of the track. Uphill gradients oppose motion, while downhill gradients assist it. For small angles, the force is expressed as:

$$F_g = mg\alpha,$$

   where m is the train mass, g is the gravitational acceleration, and α is the track gradient angle. In this case, the company's dataset provides the gradient G, expressed in ‰, which indicates how many meters the track rises (or falls) over

1000 meters of horizontal distance. This allows the calculation of the track gradient angle α as

$$\alpha = \arctan(\frac{G}{1000}).$$

Finally, applying Newton's second law, the longitudinal dynamics become:

$$m\frac{dv}{dt} = F_m - F_{\text{res}} - F_g.$$

This formulation provides the essential physical framework used later in the modeling and simulation tasks. More specific implementation details, numerical strategies, and parameterization are presented in Chapter 5.

2.3 ATO and Automatic Train Control Systems

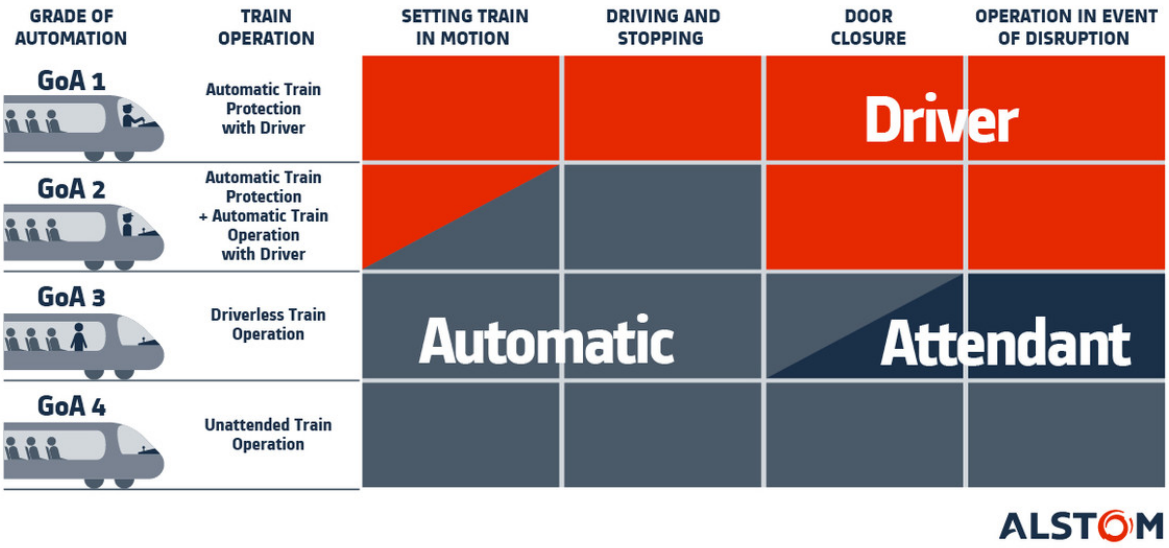
Automatic Train Operation (ATO) is a system designed to automate certain aspects of train operation, such as speed regulation, station stopping, and departure management, while fully respecting the safety constraints imposed by the train protection system. In the context of ERTMS, ATO acts in conjunction with the European Train Control System (ETCS), leveraging the supervision limits and braking curves defined by Subset-026 to safely automate driving tasks.

ATO can be seen as an operational layer on top of the existing Automatic Train Protection (ATP) functionality provided by ETCS. While ETCS ensures safety by supervising train speed, enforcing braking curves, and triggering emergency interventions if needed, ATO focuses on operational efficiency and ride comfort. Its functions include automatic regulation of speed to follow permitted profiles, precise stopping at stations, dwell time management, and energy-efficient driving by optimizing acceleration and braking within safe limits.

Train automation is classified in terms of Grades of Automation (GoA), which define the level of human involvement in train operation. GoA 0 corresponds to manual operation with no automatic intervention; GoA 1 involves manual driving with ATP supervision; GoA 2, common in current ATO deployments over ETCS Level 2, allows semi-automatic operation where the ATO controls speed and stopping while a driver supervises; GoA 3 is driverless operation with an attendant for emergencies; and GoA 4 corresponds to fully unattended train operation (UTO), where all driving tasks are automated and safety is ensured solely by ETCS and ATO systems.

In a GoA 2 ATO system integrated with ETCS Level 2, the onboard ATO continuously receives supervision data, including the braking curves (EBD/EBI), movement authorities, speed limits, and infrastructure information such as gradients and temporary restrictions. The system calculates optimal acceleration and deceleration profiles to maximize performance while remaining within the ETCS-defined safe envelope. For example, ATO can start braking later than a human driver would, exploiting the margin

Figure 6 – ATO Grades of Automation (Simoni, 2025d)



between the EBI and EBD curves, because it reacts instantly to real-time supervision updates and continuously adapts the trajectory based on train dynamics.

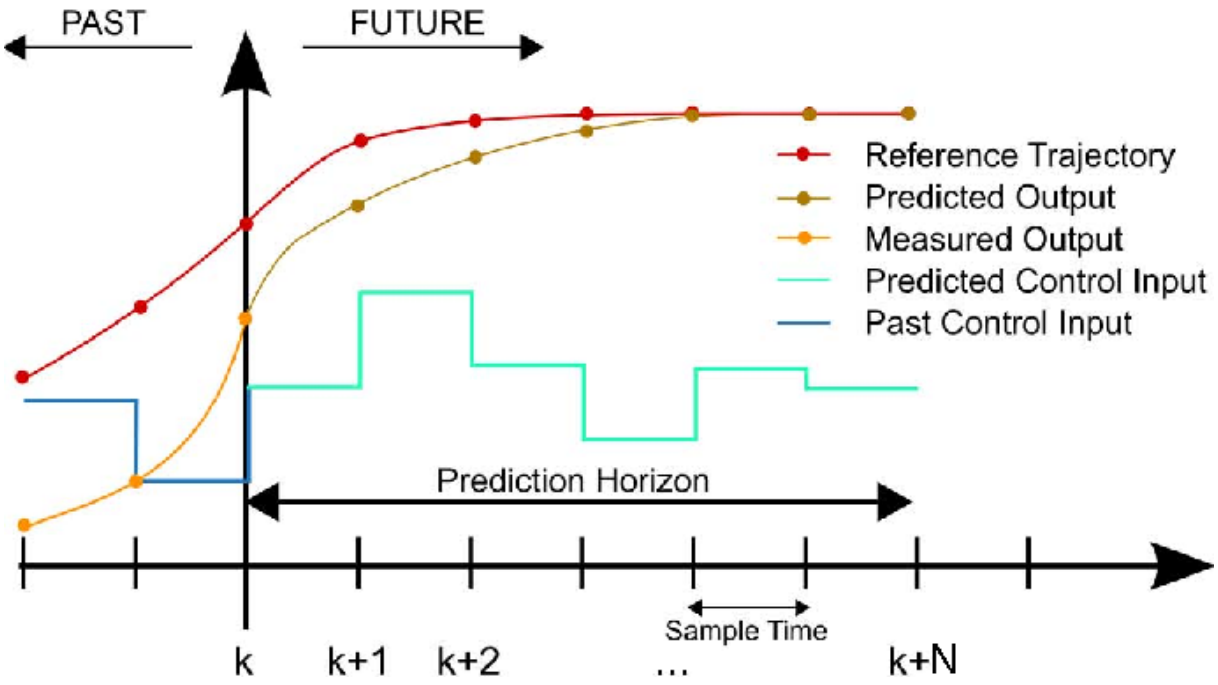
The combination of ATO and ETCS provides several operational advantages. Safety is enhanced because ATO strictly respects ETCS limits and reacts faster than a human operator. Punctuality improves due to precise speed control and optimal station stops. Energy efficiency is increased through smooth driving profiles that reduce unnecessary acceleration and braking. Additionally, traffic capacity can be optimized as consistent train handling allows shorter headways without compromising safety.

Overall, ATO represents a natural evolution of ETCS, enabling a wide range of applications, from an advisory system in GoA 1 to fully autonomous trains in higher grades. By coordinating speed, braking, and station stops within the safety envelope defined by Subset-026, ATO allows for safer, more efficient, and energy-conscious train operation, while facilitating the transition to higher Grades of Automation in future railway deployments. The focus of this study is on the transition from GoA 1 to GoA 2.

2.3.1 The MPC controller

Model Predictive Control (MPC) is a control strategy well-suited for executing the optimal speed and braking profiles generated by an ATO system. Unlike classical feedback controllers, MPC predicts the future behavior of the train over a finite time horizon, using a dynamic model of the train and the track, and computes the control inputs that optimize a given performance criterion while respecting constraints. (Camacho; Bordons, 2012)

Figure 7 – Basic concepts of a Model Predictive Controller (MPC) (Simon, 2014)



From a theoretical standpoint, MPC relies on the explicit use of a prediction model, typically written in discrete-time state-space form as

$$X[k+1] = A_d X[k] + B_d u[k] + K_d, \tag{1}$$

where $X[k]$ is the system state at time step k, $u[k]$ is the control input, and A_d, B_d, and K_d are the discrete-time system matrices obtained from the continuous-time model. At each sampling instant, this model is used to predict the future evolution of the state over a finite prediction horizon N_p.

In many practical applications, including motion control systems, it is interesting to formulate the control problem in terms of control input variations rather than absolute control values. The control increment is defined as

$$\Delta u[k] = u[k] - u[k-1]. \tag{2}$$

This incremental formulation allows the controller to directly penalize abrupt changes in the control input, improving actuator smoothness and passenger comfort.

Using the prediction model, the future states over a prediction horizon N_p can be stacked into a single vector

$$\mathbf{X} = \begin{bmatrix} X[k+1] \\ X[k+2] \\ \vdots \\ X[k+N_p] \end{bmatrix}, \tag{3}$$

while the future control increments over a control horizon $N_c \leq N_p$ are grouped as

$$\Delta \mathbf{U} = \begin{bmatrix} \Delta u[k] \\ \Delta u[k+1] \\ \vdots \\ \Delta u[k+N_c-1] \end{bmatrix}. \tag{4}$$

By recursively applying the system dynamics, the predicted state trajectory can be expressed in compact matrix form as

$$\mathbf{X} = \Psi X[k] + \Phi \Delta \mathbf{U} + \mathbf{K}, \tag{5}$$

where Ψ and Φ are the prediction matrices that describe, respectively, the influence of the current state and future control increments on the predicted states, while $\mathbf{K}$ groups the constant terms.

The control objective in MPC is typically defined through a quadratic cost function of the form

$$J = \sum_{i=1}^{N_p} \|X[k+i] - X_{\text{ref}}[k+i]\|_Q^2 + \sum_{i=0}^{N_c-1} \|\Delta u[k+i]\|_R^2, \tag{6}$$

where X_{ref} is the reference trajectory to be tracked, and Q and R are positive semi-definite and positive definite weighting matrices, respectively. The first term penalizes tracking errors, while the second term penalizes variations in the control input.

The optimization problem is subject to constraints that reflect physical limitations, safety requirements, and operational bounds, such as limits on the control input, its variation, and the system states. Once the optimization problem is solved, only the first element of the optimal control sequence is applied to the system. At the next sampling instant, the system state is updated, the prediction horizon is shifted forward, and the optimization is solved again. This strategy is known as the receding horizon principle and provides robustness to modeling errors and external disturbances.

Thanks to its ability to explicitly incorporate system dynamics, constraints, and future reference information into a single optimization framework, MPC is particularly well suited for railway applications. Track characteristics such as gradients, speed limits, and braking constraints are known in advance, allowing the controller to make accurate predictions and compute optimal control actions while strictly respecting safety envelopes imposed by railway signaling systems.

3 PROBLEM OUTLINE

This chapter provides a detailed description of the operational problem, constraints, and modeling requirements addressed by this project, which focuses on the feasibility study of ATO GoA2 implementation on the Paris–Lyon line.

This study builds on previous internal studies that highlighted energy-saving benefits of the ATO implementation, but now shifting the focus to operational gains, particularly on increasing line capacity by reducing the interval between two consecutive trains, as well as assessing the system's performance in recovering from disturbances.

3.1 Operational Context

As presented in chapter 1, the Paris-Lyon line is the busiest railway line in France, with an average of 240 trains/day, representing one third of the high-speed traffic on the French network. This 460-km line, commissioned in 1981, currently operates at near-saturation during peak hours. (SNCF Réseau, 2024)

Under the LGV+ modernisation programme, SNCF is implementing a full upgrade of infrastructure: replacement of stations, deployment of the European-standard signalling system ERTMS, installation of a Centralised Network Control centre in Lyon to manage operations, and reinforcement of the electrical supply system. (SNCF Réseau, 2024)

With the European Rail Traffic Management System (ERTMS) deployment and associated works, the capacity of the line is set to increase from currently 13 trains per hour per direction at peak times to 16 trains per hour per direction by 2030 — a 25% capacity gain — allowing more trains to run without building a new line. (SNCF Réseau, 2024)

This upgrade is also a step toward innovation, as by deploying ERTMS the railway becomes technically capable of supporting semi-automated train operation (transition from GoA1 to GoA2), by following the standard defined under ERTMS/ATO. (Simoni, 2025b)

3.2 Problem Definition

One of the key arguments in favor of automation is that human operation of trains introduces significant variability in the behavior of each train. Different operator behaviors, such as over-braking, different reaction times, or other operational actions executed more or less aggressively, can lead operators under identical timetables and the same non-disturbed external conditions to run the same trajectory with very different speed profiles. Automating train traction and braking through the implementation of ATO GoA2 can provide a standard behavior for the trains, making their operation more

predictable and bringing potential operational gains by reducing reaction times, allowing trains to run closer together, and improving performance under disrupted situations, such as delays or technical issues.

This also raises a discussion about possible ATO architectures: whether standalone (without communication) or connected to other trains. As an intermediate approach, the implementation of a Connected Driver Advisory System (C-DAS) could as well assist drivers in anticipating and adapting their driving in the event of disturbances, further enhancing operational reliability and efficiency. This C-DAS system works in real time, recalculating the information shown to an operator based on the information received from other trains.

3.2.1 Capacity Enhancement

One of the motivations for introducing ATO GoA2 on the Paris-Lyon line is its potential to increase line capacity by reducing the minimum departure interval between two consecutive trains. In high-density high-speed operations, capacity is a function of the headway, defined as the minimum time separation required for safe and stable operations. Since the theoretical line capacity C (in trains per hour) is inversely proportional to the headway H (in seconds):

$$C = \frac{3600}{H},$$

even small reductions in headway translate directly into significant capacity gains. For example, when close to the current operating point of 13 trains/hour, each headway reduction of around 20 seconds increases the theoretical capacity by around one train per hour.

On the Paris-Lyon line, the practical headway is not limited solely by signaling constraints (such as braking distance or block occupation time), but also by the variability in train driving behavior. Under manual operation, dispersion in reaction times, braking anticipation, and adherence to the speed profiles leads to fluctuations in running time and speed trajectories. This variability forces the line operators to incorporate margins between trains to avoid catching up.

The working hypothesis of this study is that ATO GoA2 will not only reduce the average headway, by standardizing traction and braking commands, but also impact its variance, since trains will follow repeatable and tightly controlled speed profiles. In sections where trains must adapt rapidly to gradients, speed restrictions, or other sudden changes, the effect of reduced dispersion is particularly impactful, enabling trains to operate closer to the theoretical limits without compromising safety or robustness. The results will help assess the realistic gains that automation can bring to a saturated high-speed corridor such as the Paris-Lyon line.

3.2.2 Delay recovery and perturbation management

In addition to nominal capacity gains, an important aspect of this study is the ability of ATO GoA2 to improve the system's behavior under perturbed conditions. Today, there is no defined guideline for delay recovery on the Paris-Lyon line, meaning that it depends largely on the driver's individual strategy. When running late, drivers may attempt to regain time by keeping a speed closer to the limit, but the way they do it may vary significantly from one driver to another. As a result, recovery performance is heterogeneous and difficult to predict, which complicates traffic regulation and increases the risk of delay propagation to following trains.

The working hypothesis of this project is that ATO GoA2 can standardize and optimise these recovery strategies. By applying consistent driving rules, reacting faster to signalling constraints, and controlling speed with higher precision, an ATO-equipped train should be able to recover minor delays more efficiently and in a more reproducible manner. This is particularly relevant for small perturbations, where controlled adjustments in traction and braking can allow the train to regain part of the delay before reaching key timing points.

For larger delays or for disturbances that affect the line, full recovery may not be possible through driving strategy alone; however, a predictable and stable response from the train remains beneficial for traffic management. The challenge lies in the fact that, under the current ERTMS architecture, the ATO system operates with mainly local information and has no direct information exchange with other trains. This limits its ability to coordinate recovery with other trains, an aspect that motivates the discussion of alternative ATO and C-DAS architectures in the next subsection.

3.2.3 Possibilities of ATO/C-DAS architectures

The discussion on delay recovery naturally leads to the question of how different ATO architectures could influence operational performance on the Paris-Lyon line. As presented in Chapter 2, the ERTMS/ATO standard defines several possible levels of integration between the train, the infrastructure, and external information sources. These range from manual operations and standalone ATO, operating with on-board optimisation only, to more advanced architectures such as Connected Driver Advisory System (C-DAS) or fully network-integrated ATO systems.

In the current configuration of the Paris-Lyon line, information exchange is limited to communication between the train and the trackside. The train receives its movement authority and information about the track, but has no direct communication with other trains nor access to global traffic information. Under such conditions, a standalone ATO GoA2 can standardize driving behavior and improve local delay recovery, but it remains constrained by the fact that it optimises its trajectory with only local data. As highlighted

in the previous subsection, this limits its ability to anticipate the behavior of preceding or following trains, and therefore restricts its contribution to network-wide perturbation management.

A more advanced alternative is to upgrade the information flow, allowing trains to exchange real-time operational conditions. In manual operation, it would be a C-DAS architecture, which provides the driver with additional information such as traffic conditions, expected conflicts, or recommended speed adjustments aligned with the global timetable. By associating this upgrade in information exchange with ATO strategies, with movement authorizations and optimisation objectives continually updated using system-wide data, recovery strategies could become both more efficient and better coordinated with the rest of the traffic. This represents the most ambitious option, but also the one requiring the largest infrastructure and organisational changes.

In this study, the modeling focuses primarily on the standalone ATO GoA2 case, as it corresponds to the architecture compatible with the first deployment phase of ERTMS on the Paris-Lyon line. However, understanding the potential benefits and limitations of each architecture is essential for interpreting the results and for identifying which operational gains are achievable today and which depend on future system evolution.

3.3 Modeling Requirements and Data Sources

To evaluate the potential operational gains associated with the introduction of ATO GoA2 on the Paris–Lyon line, the simulation model must represent the behavior of trains, the characteristics of the infrastructure, and the operational context in which both operate. The objective is to build a modeling environment capable of representing the key elements that influence headways, delay propagation, and recovery strategies.

A realistic representation of train dynamics is important to evaluate how different driving strategies (manual or automated) affect running times and headways. The model must reproduce the fundamental relationships between traction effort, braking capability, mass, gradient and speed, allowing trains to follow feasible acceleration and deceleration profiles. In addition, the dynamics must be fully compatible with the signalling supervision imposed by ERTMS, ensuring that speed limits, braking curves, and movement authority boundaries are correctly respected.

To physically represent the line, the infrastructure model includes all relevant characteristics of the Paris-Lyon high-speed line: track geometry, gradients, speed restrictions, and ERTMS operational parameters. These elements define the constraints within which trains operate and directly affect achievable running times, braking distances, and thus the theoretical minimum headway.

The rolling stock is modelled using detailed performance parameters, such as traction and braking characteristics, mass, maximum speed, and running resistance

coefficients. The parameters used were extracted from the company's internal dataset, produced through dedicated modeling efforts to characterise the rolling stock, and are therefore considered reliable for modeling purposes. Accurate train data ensure that the simulated behavior remains consistent with real operational capabilities and allows for a fair comparison between manual driving and ATO-regulated speed profiles.

4 PROPOSED SOLUTION AND METHODOLOGY

The main objective of this project is to evaluate the potential operational gains of Automatic Train Operation (ATO) in comparison with manual train operation on a high-speed line. To address this problem, a systematic methodology has been defined, consisting of model development, scenario definition, manual operator characterization, and performance evaluation. Along with being a proposed solution to the problem presented in chapter 3, these steps are also aligned with the objectives of this project, as presented in chapter 1.

4.1 Main steps of the solution

To begin, the problem was decomposed into manageable components, each of which can be modeled and analyzed independently, while maintaining their interactions within the overall system. A five-month plan was developed at the beginning of the internship and dynamically modified as the project evolved, resulting in the following components:

- **Onboarding:** familiarization with railway operations, signaling and important concepts such as the ERTMS (European Rail Traffic Management System) guidelines, braking curves, ATO (Automatic Train Operation) principles, operational procedures, and so on, along with an initial literature review and current data analysis to frame the problem.
- **Modeling of a train:** modeling of train motion based on traction, braking, resistive forces, and track gradients.
- **Railway line and traffic management:** modeling line geometry and parameters from real data, allowing centralized traffic control through Movement Authorities and multiple train interactions.
- **Human operator behavior:** capturing variability in manual driving through behavioral models derived from empirical data.
- **Automatic Train Operation:** proposing a strategy to follow an optimal speed profile while respecting safety and separation constraints.

4.2 Modeling Methodology

The objective is to iterate over simulation results to refine the model and parameters. This ensures that the final model is representative of actual behavior, and suitable for assessing the operational benefits of automation.

The methodology follows a modular modeling strategy, where each component is implemented as a separate block that can be integrated into a larger simulation framework. This modularity allows:

- Progressive refinement of models, starting from a simple train dynamics model to more complex scenarios involving multiple trains and operator variability.
- Testing different control strategies, including manual operation, behavioral operator models, and ATO algorithms.
- Flexible scenario simulation to evaluate operational performance under varying traffic, train types, and operator profiles.

4.2.1 Data collection and parameters

A key part of the methodology is the use of real-world operational data to parameterize both train dynamics and human operator models. This includes:

- Train performance data (traction, braking, resistances), obtained from the company's *Opticonduite* database.
- Track data (gradient, section lengths), obtained from SNCF Open Data (SNCF Open Data, 2025)
- Operator speed and position profiles under normal operation conditions, provided by the company through the *Acquisition et Traitement des Evénements de Sécurité en Statique* (ATESS) system.

These data allow calibration of the models to ensure realistic simulation results.

4.2.2 Scenario definition and performance metrics

The methodology relies on simulation as the primary evaluation tool. Once models are defined and parameterized, scenarios are designed to test the performance of both manual and automated operations. Key aspects include:

- Single-train and multi-train operations to evaluate traffic interactions.
- Variation of departure intervals and operator profiles.
- Testing in nominal or disturbed situations to observe different behaviors of the trains.

The identification of performance metrics is also an important part of the process, to allow the quantification of the potential gains. Some preliminary indicators that can be discussed are:

- Adherence to timetable, by measuring the time difference between the scheduled and the real time when a train passes through all the timing points present in a mission. Usually, respecting the timetable means passing through certain points with a maximum deviation of $\pm$ 1 minute of the scheduled time. More than this interval can be considered a non-optimized scenario.
- Capacity gain, assessed via interval reduction, i.e., how much train headways can be decreased without forcing trains to slow down due to proximity. Maximum capacity is defined as the highest train frequency (or lowest headway) that does not generate perturbations, defined as deviations from schedule or speed limits affecting performance. This provides a quantitative measure of potential throughput improvement.

5 DEVELOPMENT AND RESULTS

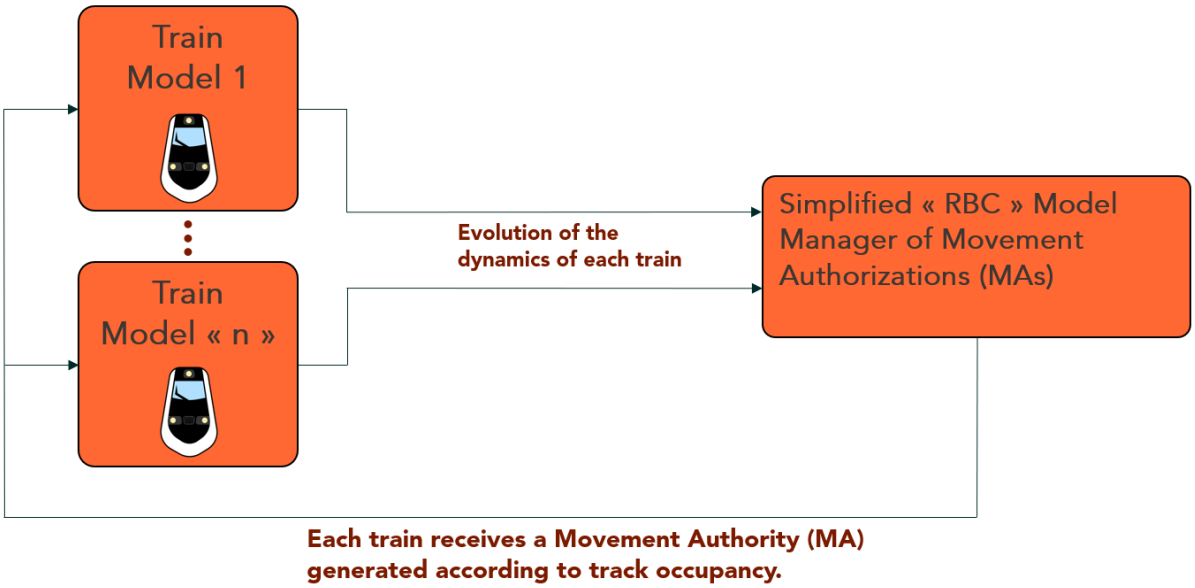
This chapter presents the development of the simulation framework used to analyze train operation under manual driving and Automatic Train Operation (ATO). The objective is to model both the behavior of individual trains and their interactions within a railway line, in order to evaluate traffic management strategies, safety constraints, and control performance.

The modeling approach follows a hierarchical structure. A global model of the Paris–Lyon high-speed line represents the infrastructure and traffic supervision logic, including the management of Movement Authorities by a Radio Block Center (RBC). At a lower level, each train is modeled individually, capturing its dynamics, onboard supervision, and driving behavior, whether human or automatic.

This chapter is organized as follows: first, the train line model and its traffic management principles are introduced. Then, the train model is presented in detail, including each of its components. Finally, operation strategies are introduced, followed by the obtained simulation results.

5.1 Train Line Model Development

Figure 8 – Overview of the model structure, with the Radio Block Center (RBC) that acts as a traffic controller



At the highest level, a train line model represents the infrastructure and traffic management logic, including the allocation of Movement Authorities (MAs) through a centralized Radio Block Center (RBC). This setup allows the investigation of train interactions, including spacing, delays, and effects of varying departure intervals. By adjusting parameters such as the number of protected sections or departure spacing,

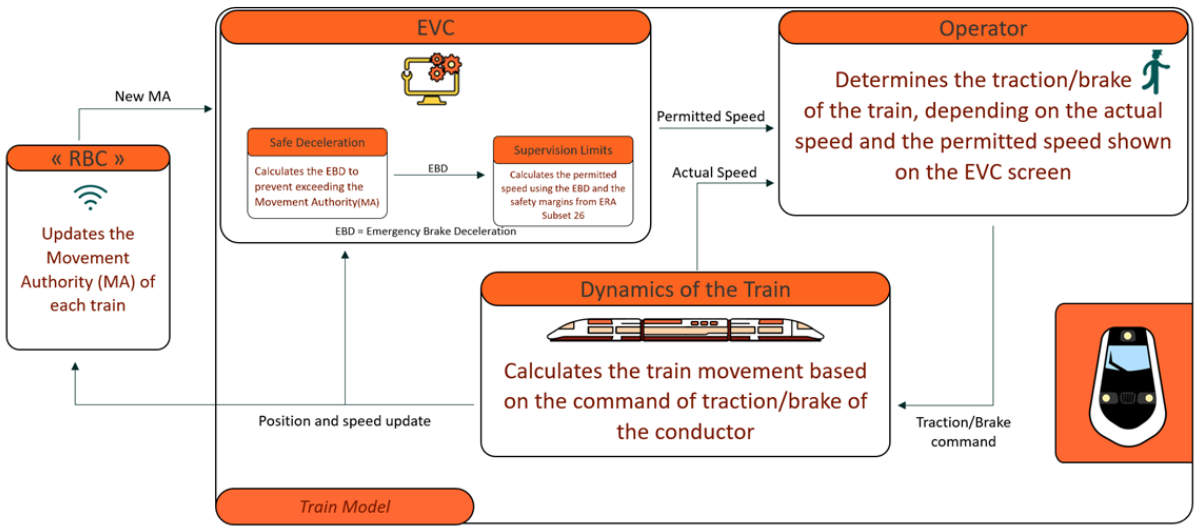
the model can simulate real-world traffic scenarios and assess the impact on line capacity and operational performance.

The model is represented by figure 8. There is one instance of the train model for each simulated train, in addition to one Radio Block Center (RBC) that manages the traffic on the line. It does so by sending a Movement Authority (MA) to each train based on its current position and the occupation of the line, always keeping a safe distance between the trains. The line is divided by sections, and the train only gets a new MA if the *n* following sections for its path are free. The idea here is that multiple trains can be following each other and changing the parameters such as the departure time spacing or the *n* sections that are guarded between the trains, allowing the observation of how the trains interact with each other, and which effects appear. The usual *n* for trains in the ERTMS system is 7 sections, translated into approximately 17km of physical distance in average.

5.2 Train Model

The train model was initially developed as a basic simulation of train movements on a parametrizable line, without optimization, to serve as a foundation for later refinements. The objective was to reproduce the operational conditions of the LGV+ between Paris and Lyon. This model allows the evaluation of train performance under manual operation and provides a baseline for the subsequent implementation of Automatic Train Operation (ATO). By comparing manual and automatic scenarios, potential operational gains can be quantified, providing a technical justification for ATO implementation. The train model architecture is shown on Fig. 9, and will be explained in this section.

Figure 9 – Schematic of the train model under manual operation



The train model is structured into three main components: the European Vital Computer (EVC), the Operator, and the Train Dynamics. The modeling of each compo-

nent is presented in the following subsections. The underlying technical concepts from Chapter 2 are briefly recalled when relevant. A full description of the overall architecture can be found in that chapter.

5.2.1 European Vital Computer (EVC)

The European Vital Computer (EVC) block is what represents the on-board computer, that displays all the relevant information to the operator, and triggers the emergency braking when needed. This block is the one that receives and processes the information from the trackside equipment, to calculate the speed limits and relevant information to display to the operator, as well as acting as a safety device. In this model, the EVC is composed by 2 blocks - the “Safe Deceleration” block, and the “Supervision Limits” block. Both of these blocks will interact with the real-time information from the train model, such as actual speed and position, and the Movement Authority (MA) issued by the manager block, the Radio Block Center (RBC). Both blocks have its architecture defined by the European Railway Agency (ERA) Subset-26 (European Union Agency for Railways (ERA), 2016), specifically on its chapter 3.

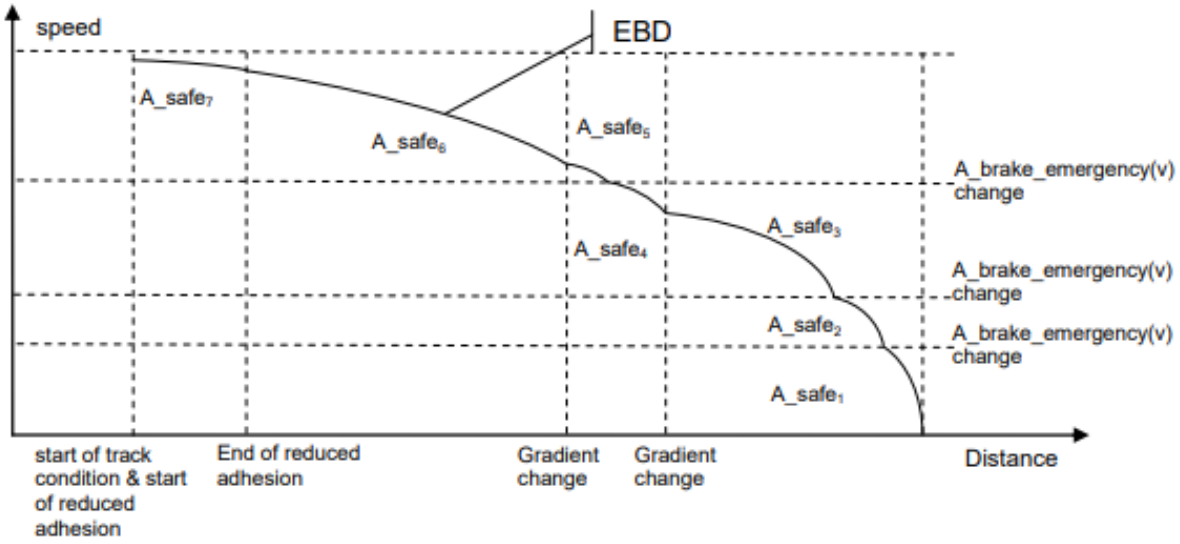
The first one, “Safe Deceleration”, takes the train’s braking parameters and the limits of authority of the train to calculate in real time the emergency brake deceleration (EBD) curve, taking two components into consideration:

- The train’s braking capacity, which depends on its current speed and is corrected by coefficients that take the rail adherence and other factors into consideration, such as wet/dry rails, which depend on the train’s position.
- The effect of the track gradient, that is also a function of the position. This effect is negative when the train is going downhill and positive when the train is going uphill, meaning that the same braking effort will be more or less effective depending on the gradient.

Under this representation, the guidelines of the Subset-26 allow us to consider both the braking capacity and the gradient effect as piecewise constant, building a grid, and finding the safe deceleration of the train as a sum of both components. An example of an EBD curve is on Fig. 10, extracted from section 3.13.6.2.1 of the Subset-26. The grid shown is constructed taking into account the different braking capacities as a function of the speed (y-axis) and as a function of the position of the train (x-axis), that causes the gradient and adhesion conditions to change. Inside each cell, the train’s safe deceleration limit is considered to be constant.

This EBD is then used as input on the “Supervision Limits” model, that once again takes the ERA Subset-26 values to calculate the permitted speed, displayed on the screen to the operators and followed by them to ensure the safety of the train. This

Figure 10 – Example of EBD curve, that takes into account different deceleration capacities for each cell of the grid.(European Union Agency for Railways (ERA), 2016)



block gets this permitted speed value by considering the safe deceleration that was just calculated along with other parameters such as reaction times and transmission delays to create a safety margin. The human reaction time considered on these calculations is one of the parameters that will disappear once the ATO is implemented, making the system able to have a reduced safety margin. The details on the calculation of the supervision limits are on Chapter 2, with an explanation of how the indications shown on the DMI screen are calculated, highlighting the human reaction times taken into consideration. An ATO implementation will allow the trains to be more responsive to the indications, thus reducing the need of anticipating the braking points.

5.2.2 Train Dynamics

Going further into the dynamics of the train block, it is responsible for calculating the evolution of the speed and position by using basic physics principles such as the second Newton's law, as presented in chapter 2. We consider that there are 3 forces acting on the train when it is moving: a force F_m coming from its traction/braking, that depends on the operator's action (here represented by M) and on the current speed, along with a resistive force F_{res} that always opposes the speed of the train. The third force F_g comes from the track gradient, that can speed the train up or down depending on the current position of the train. The model is then:

$$m\ddot{x} = F_m(M, \dot{x}) - F_{\text{res}}(\dot{x}) - F_g(x), \tag{7}$$

where x is the position of the train and its derivatives of first and second degree are respectively the speed and acceleration of the train. Each force is then calculated as

follows:

$$F_m(M, \dot{x}) = \begin{cases} T(\dot{x}) \cdot M, & M \geq 0 \\ F(\dot{x}) \cdot M, & M < 0, \end{cases} \tag{8}$$

where T and F are the maximum traction and brake characteristics, that depend on the speed, meaning that depending on the speed a train can have a maximum effort that is known from the available data given by the manufacturers. This effort is then multiplied by a variable M, that ranges from -1 to 1, representing the operator's input: 1 being 100% acceleration, and -1 being 100% brake. This 'M' value will later be used as the control input of the system.

$$F_{\text{res}}(\dot{x}) = A + B\dot{x} + C\dot{x}^2, \tag{9}$$

as A, B and C are known parameters of the train, given by the company as part of studies of the trains, accounting for friction and drag.

$$F_g(x) = mg \sin(\alpha(x)) \approx mg\alpha(x) \tag{10}$$

$$\text{as } \alpha(x) = \arctan(G(x)), \tag{11}$$

as m and g are known and α is the slope angle of the track. The small angles approximation $sin(x) \approx x$, in radians, is used. Thus, the gravitational force F_g is calculated as shown, with G being the gradient value of the track, in ‰, depending on the current position of the train. Finally, with these three components the acceleration can be calculated, being twice integrated to yield the updated speed and position.

5.2.3 Operator Modeling

The third block of the model corresponds to the operator. In the initial stages of development, the operator was represented as a simple proportional controller acting on the difference between the permitted and actual speeds. This yielded a control input M ranging from full traction to full braking. This simplified representation was sufficient to validate the dynamics model, to study interactions between trains, and to verify the overall evolution of a train along the track. However, to accurately represent the human factor and to develop a realistic manual-operation model, more advanced operator-modeling approaches were required.

With the availability of a significant amount of real operational data of speed and position of the trains, several attempts were made to reverse-engineer the operator's actions by reconstructing the train's control input from measured trajectories. Since acceleration could be obtained as the derivative of the measured speed, and given that speed, position, and train parameters were known and/or measured, resistive

and gravitational forces could be approximately computed. This made it theoretically possible to reconstruct the motor force and infer the operator's control input.

In practice, however, this approach did not produce satisfactory results. The acceleration obtained from differentiating real speed data carried measurement noise and propagated uncertainty into the reconstructed forces. Moreover, the reconstruction relied on traction and braking curves specific to each train, introducing additional errors, along with other sources such as wind influence, mass variations, etc. When the reconstructed input profiles were tested back into the model, the resulting simulated speed profiles deviated significantly from the real ones. For these reasons, this reverse-engineering approach was abandoned.

A second alternative emerged from empirical observations of real-world behavior of the trains. When an operator is in a speed-maintenance phase, with a permitted speed displayed on the screen, the operator does not aim at this limit directly. Instead, each operator appears to adopt a personal "target speed" slightly below the permitted value, oscillating around it with a certain amplitude and frequency. From the analysis of a set of 20 operators, the difference between the permitted speed and the effective target speed, as well as the oscillation intensity and frequency, could be statistically characterized by an average and a variance.

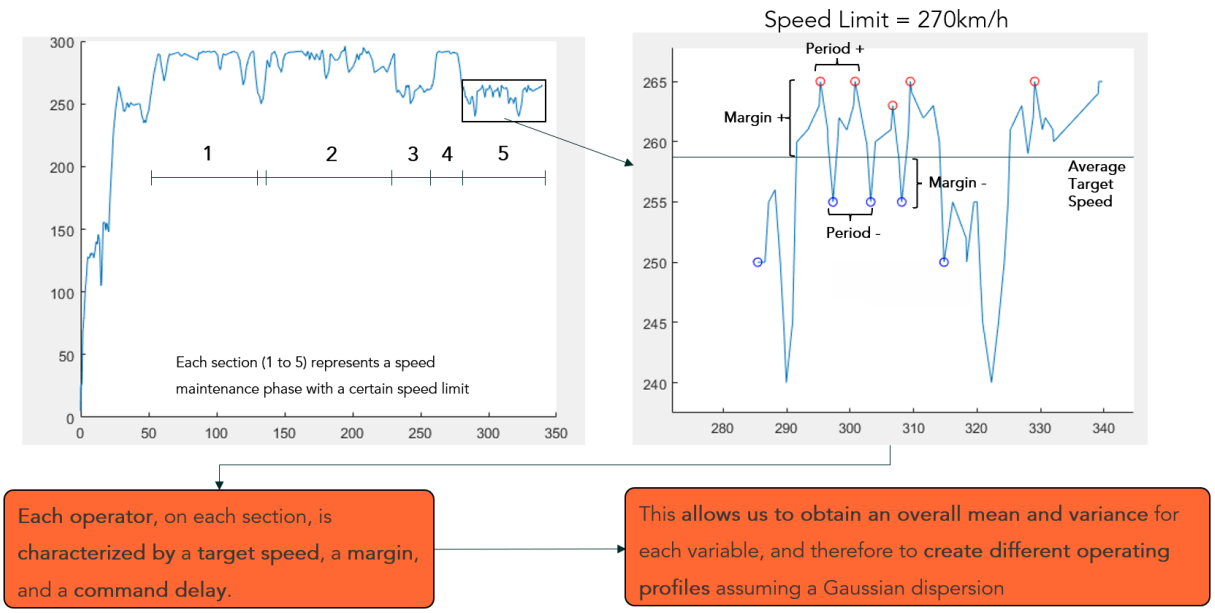
Based on this observation, a behavioral operator model was developed. Five sections of the Paris-Lyon trajectory where speed-maintenance behavior occurs were identified, and each real operator was characterized in each section by a triplet of parameters:

1. a target speed (below the permitted speed),
2. an oscillation amplitude (around the target speed),
3. and a control delay (an average time between two control actions), derived from the oscillations period.

The dataset consisted of undisturbed-traffic runs from a chosen train operating between Paris and Lyon.

From Fig. 11, we identify on the left plot the division of a Paris-Lyon trip in 5 speed-maintenance sections, where each operator had its parameters identified. The zoomed-in view on the right illustrates how target speed, positive and negative margins, and oscillation periods are extracted for a given section. These metrics are then used to characterize each operator by a target speed, a margin, and a command delay in each section, enabling the derivation of overall statistical parameters and the generation of operating profiles assuming Gaussian dispersion. The oscillation around the target speed is then reproduced using a sinusoidal component whose amplitude and frequency are likewise drawn from the corresponding distributions, allowing realistic operating profiles to be generated.

Figure 11 – Example of identification of target speed, margins, and control delay across driving sections for a real operator.



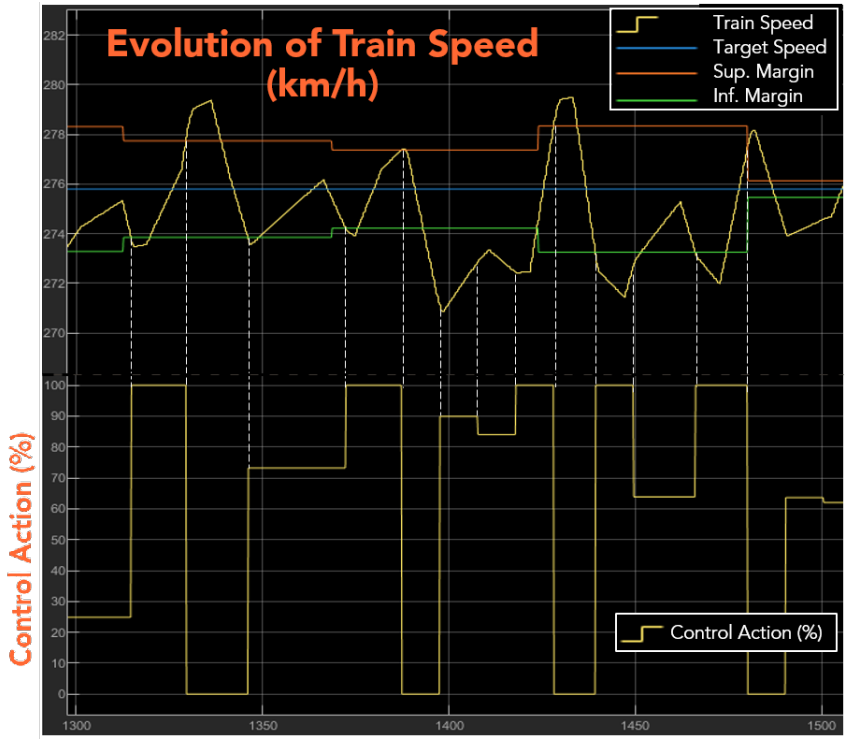
Then, given a set of operator parameters, the conversion back to a control action followed observed operational logic:

- If the train speed exceeds the upper margin around the target speed, the operator commands coasting ($M = 0$).
- If external forces (e.g., downhill gradients) cause further acceleration despite coasting, the operator applies braking to avoid exceeding the speed limit.
- When speed falls below the lower margin, the operator computes a new input based on the target speed, the current speed, and the control delay, estimating the required acceleration to keep the speed on its desired interval. After accounting for resistive and gravitational forces, the desired motor force is converted into a control command issued by the virtual operator.

From Fig. 12, we observe that external conditions - such as track gradient - lead the operator to apply a best-effort strategy to remain within the defined margins, alternating between traction and coasting in a manner consistent with the behavior inferred from real operators' data.

Finally, using these generated profiles, several simulation scenarios were run. Validation relied on timetable compliance: an operator was retained only if its simulated train respected all timing-point constraints of the real mission. This selection ensured that the generated operators were both realistic and operationally feasible. Another aspect that can be further discussed is the behavior when outside the required timetable. For this study, when a timing point is passed late, the operator closely follows the

Figure 12 – Example of the operation of a train following a generated set of parameters



maximum speed until recovery, whereas passing it early leads the operator to reduce its target speed.

Within the validated operator set, multiple two-train following scenarios were tested. One of the most insightful results emerged when combining different operator types. For instance, an “average” operator leading the train followed by an “aggressive” operator - characterized by a higher target speed and shorter control delay - produced a significant reduction in the time separation between trains. More on the headway and capacity analysis will be discussed in section 5.3.2

5.2.4 Automatic Train Operation model

The ATO model builds upon the train and line models to simulate automated control according to GoA2 standards. The system computes the energetically optimal traction and braking commands to follow a predefined speed profile, maintaining safe separation between trains while minimizing travel time and maximizing line capacity. By comparing results from ATO with those from the human operator model, the potential gains in efficiency, regularity, and safety can be quantified. Several ATO architectures can be considered, such as standalone operation or connected operation with a C-DAS (Connected Driver Advisory System), to evaluate performance under normal and disturbed conditions. In this study, the ATO is assumed to operate in a standalone configuration, meaning that information is exchanged only between train and the wayside equipment, with no train-to-train communication. Other architectures will be discussed

in each scenario whenever they are relevant or could potentially outperform the standalone ATO.

For this study, two modeling approaches were proposed. The first corresponds to an ideal implementation, in which the train follows the exact pre-calculated energetically optimal speed profile whenever possible, except when interventions from the EVC impose a lower permitted speed. This implementation was the one used on the study for capacity gains and yielded the results presented in the next section. The second implementation is a Model Predictive Controller (MPC), developed to better approximate a realistic control behavior capable of validating the feasibility of these ideal profiles.

5.2.4.1 The MPC implementation

Having established a realistic baseline for manual operation and an idealized reference for automatic driving, this section presents the development of a Model Predictive Control (MPC) strategy aimed at bridging the gap between ideal performance and a realistic closed-loop implementation. This formulation was developed after the main objectives of the project had been achieved and the different scenarios had been tested and evaluated. The primary purpose of this MPC design is to assess the feasibility of the previously assumed “optimal speed profile” when used as a reference in a feedback control framework, and to provide a preliminary step toward a more realistic automation and control architecture.

To this end, a simplified linear MPC formulation was adopted as an initial, lower-complexity control approach. This methodology requires the system to be described in a state-space representation and approximated by a linear model around selected operating points. To do so, the nonlinear train dynamics were reformulated and linearized, with some parameters defined as functions of the current operating condition. At each sampling instant, the model is linearized at the current state and the corresponding control input is computed, by solving an optimization problem over the predictions of the system.

The main objective of this MPC implementation is to validate the practicality of the proposed speed reference by using it as a target trajectory and minimizing the tracking error through feedback control. As such, the present controller should be regarded as a proof of concept focused primarily on speed tracking performance. While this demonstrates that the reference profile can be followed in closed loop, further refinements would be necessary to explicitly address additional aspects such as energy efficiency, actuator smoothness, and wear reduction in a more comprehensive ATO design.

First, from the train dynamics equations, presented at section 5.2.2, it is possible to write the system in a state-space form, with the state vector

$$X = \begin{bmatrix} x \\ v \end{bmatrix}, \tag{12}$$

with the state variables being position and speed, that are linked by the kinematic relation $v = \dot{x}$. The control input is a scalar, u, that represents the traction or braking input. This value is limited to the interval $u \in [-1, 1]$. Then, the initial non-linear state-space representation can be written as:

$$\dot{X} = \begin{bmatrix} \dot{x} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} v \\ \frac{1}{m}(F_{max}(v)u - (A + Bv + Cv^2) - mg\alpha(x)) \end{bmatrix}. \tag{13}$$

In this case, $F_{max}(v)$ represents the maximum traction or braking effort that can be made as a function of the current speed. This unifies both notations $T(\dot{x})$ and $F(\dot{x})$ presented before, to simplify the calculations, and introduce the control input u. The following step is to linearize the system using a Taylor expansion, yielding the following development to obtain the system in the form $\dot{X} = AX + Bu + K$.

$$\dot{X} = \begin{bmatrix} \dot{x} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -g \left.\frac{d\alpha}{dx}\right|_{x=x_0} & \frac{1}{m}(-B - 2Cv_0) \end{bmatrix} \begin{bmatrix} x - x_0 \\ v - v_0 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m}F_{\max}(v_0) \end{bmatrix} u + \begin{bmatrix} v \\ \mathrm{f}(x, v) \end{bmatrix}. \tag{14}$$

Note that the linearized model may not be asymptotically stable in open loop. Because of the way the track angle α is modeled, it may be locally constant, leading to a zero derivative with respect to x and, consequently, to an integrator associated with the position state. However, closed-loop stability is ensured by the MPC formulation through the optimization cost and constraints, which will be presented later in this chapter. Finally, by rewriting each component of the state-space, we have:

$$A = \begin{bmatrix} 0 & 1 \\ -g \left.\frac{d\alpha}{dx}\right|_{x=x_0} & \frac{1}{m}(-B - 2Cv_0) \end{bmatrix}, \tag{15}$$

$$B = \begin{bmatrix} 0 \\ \frac{1}{m}F_{\max}(v_0) \end{bmatrix}, \tag{16}$$

and

$$K = \begin{bmatrix} 0 \\ \frac{1}{m}(-A + Cv_0^2) - g(\alpha(x) - x \left.\frac{d\alpha}{dx}\right|_{x=x_0}) \end{bmatrix}. \tag{17}$$

Finally, the next step to apply the MPC controller is to discretize the system with a sampling time T_s. Thus, the conversion from continuous to discrete-time is made as follows:

$$\dot{X} = AX + Bu + K \xrightarrow{T_s} X[k+1] = A_d X[k] + B_d u[k] + K_d, \tag{18}$$

as

$$X[k] = \begin{bmatrix} x[k] \\ v[k] \end{bmatrix} = \begin{bmatrix} x(kT_s) \\ v(kT_s) \end{bmatrix}, \tag{19}$$

and

$$A_d = e^{AT_s}, \qquad B_d = \int_0^{T_s} e^{A\tau} B \, d\tau, \qquad K_d = \int_0^{T_s} e^{A\tau} K \, d\tau. \tag{20}$$

After discretization, the state-space model is given by

$$X[k+1] = A_d X[k] + B_d u[k] + K_d. \tag{21}$$

In this formulation, the control input is expressed in terms of its absolute value $u[k]$. However, in Model Predictive Control applications, it is often preferable to optimize the variation of the control input rather than its absolute magnitude. This approach makes it possible to penalize abrupt changes in the control signal, improves robustness, and facilitates the handling of constant disturbance terms.
For this purpose, an incremental formulation is adopted by defining the control input variation as

$$\Delta u[k] = u[k] - u[k-1]. \tag{22}$$

In order to explicitly incorporate this relation into the prediction model, the state vector is augmented by including the previous control input. The expanded state vector is defined as

$$X_e[k] = \begin{bmatrix} X[k] \\ u[k-1] \end{bmatrix}. \tag{23}$$

Using this augmented state, the discrete-time dynamics can be rewritten as

$$\begin{aligned} X[k+1] &= A_d X[k] + B_d \big(u[k-1] + \Delta u[k]\big) + K_d, \\ u[k] &= u[k-1] + \Delta u[k]. \end{aligned} \tag{24}$$

Combining the previous equations yields the augmented state-space representation

$$X_e[k+1] = A_{de} X_e[k] + B_{de} \Delta u[k] + K_{de}, \tag{25}$$

where the expanded system matrices are given by

$$A_{de} = \begin{bmatrix} A_d^{[2\times 2]} & B_d^{[2\times 1]} \\ 0 \quad 0 & 1 \end{bmatrix}, \qquad B_{de} = \begin{bmatrix} B_d \\ 1 \end{bmatrix}, \qquad K_{de} = \begin{bmatrix} K_d \\ 0 \end{bmatrix}. \tag{26}$$

In this augmented formulation, the control variable of the MPC problem is the input increment $\Delta u[k]$, while the absolute control input $u[k]$ is recovered by accumulation.

Based on the augmented discrete-time model derived previously, the next step consists of formulating the prediction model used by the MPC and defining the associated optimization problem.

Let the prediction horizon be denoted by N_p and the control horizon by $N_c = N_p = N$. Using the augmented state-space representation from eq. 25, the future evolution of the system over the prediction horizon can be written by successive substitutions.

Defining the stacked vectors

$$\mathbf{X}_h[k+1] = \begin{bmatrix} X_e[k+1] \\ X_e[k+2] \\ \vdots \\ X_e[k+N] \end{bmatrix}, \qquad \Delta\mathbf{U}[k] = \begin{bmatrix} \Delta u[k] \\ \Delta u[k+1] \\ \vdots \\ \Delta u[k+N] \end{bmatrix}, \tag{27}$$

the prediction model can be compactly expressed as

$$\mathbf{X}_h[k+1] = \Psi X_e[k] + \Phi\Delta\mathbf{U}[k] + \mathbf{K}_h, \tag{28}$$

where Φ and Ψ are the prediction matrices, and $\mathbf{K}_h$ gathers the contributions of the constant disturbance term K_{de}.

The matrix Ψ is defined as

$$\Psi = \begin{bmatrix} A_{de} \\ A_{de}^2 \\ \vdots \\ A_{de}^N \end{bmatrix}, \tag{29}$$

while the matrix Φ has a lower block-triangular structure given by

$$\Phi = \begin{bmatrix} B_{de} & 0 & \cdots & \cdots & 0 \\ A_{de}B_{de} & B_{de} & \cdots & \cdots & 0 \\ A_{de}^2B_{de} & A_{de}B_{de} & B_{de} & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ A_{de}^{N-1}B_{de} & A_{de}^{N-2}B_{de} & \cdots & A_{de}B_{de} & B_{de} \end{bmatrix}. \tag{30}$$

The vector $\mathbf{K}_h$ is expressed as

$$\mathbf{K}_h = \begin{bmatrix} K_{de} \\ A_{de}K_{de} + K_{de} \\ \vdots \\ \sum_{i=0}^{N-1} A_{de}^i K_{de} \end{bmatrix}, \tag{31}$$

and accounts for constant disturbances such as rolling resistance and track gradient effects.

The objective of the MPC is to track a reference trajectory generated by the ATO algorithm that calculates the optimal operation profiles over a finite prediction horizon. Let $X_{e,\text{ref}}[k]$ denote the augmented reference state at time step k.

The control objective is formulated as the minimization of a weighted sum of squared norms of the tracking error and the control input variations over the prediction horizon:

$$J = \sum_{i=1}^{N} \left\| X_e[k+i] - X_{e,\text{ref}}[k+i] \right\|_Q^2 + \sum_{i=0}^{N-1} \left\| \Delta u[k+i] \right\|_R^2, \tag{32}$$

where $\|z\|_Q^2 = z^\top Q z$, with $Q \succeq 0$, and $\|z\|_R^2 = z^\top R z$, with $R \succ 0$.

To express the cost function in a compact matrix form, the predicted states stacked in the $\mathbf{X}_h$ vector are compared to the reference values, that are stacked over the prediction horizon as

$$\mathbf{X}_{ref}[k] = \begin{bmatrix} x_{ref}[k] \\ v_{ref}[k] \\ u_{ref}[k-1] \end{bmatrix}, \qquad \mathbf{X}_{h,\text{ref}}[k+1] = \begin{bmatrix} X_{ref}[k+1] \\ X_{ref}[k+2] \\ \vdots \\ X_{ref}[k+N] \end{bmatrix}. \tag{33}$$

By substituting the prediction model into the cost function, the MPC optimization problem can be expressed as a standard quadratic programming (QP) problem:

$$J = \frac{1}{2} \Delta \mathbf{U}^\top H \Delta \mathbf{U} + f^\top \Delta \mathbf{U}, \tag{34}$$

with

$$H = 2\left(\Phi^\top Q \Phi + R\right), \tag{35}$$

$$f = 2\Phi^\top Q \left(\Psi X_e[k] + \mathbf{K}_h - \mathbf{X}_{h,\text{ref}}[k]\right). \tag{36}$$

The optimization problem is subject to physical and operational constraints reflecting the limitations of the train and the signaling system. These constraints include:

- **Bounds on the control input:**

$$-1 \leq u[k] \leq 1, \tag{37}$$

  where the control input $u[k]$ represents the normalized traction or braking command, with $u = 1$ corresponding to maximum traction and $u = -1$ to maximum braking.

- **State constraints:**

$$0 \leq v[k] \leq v_{\max}[k], \tag{38}$$

  where $v_{\max}[k]$ denotes the maximum permitted speed at the current position, as imposed by infrastructure limits and ETCS braking curves. The current speed $v[k]$ must respect this limit, in addition to never being negative.

These constraints can be expressed as linear inequalities on the decision variable $\Delta \mathbf{U}$, allowing the MPC problem to be formulated as a constrained quadratic programming (QP) problem and solved efficiently in real time.

Finally, at each sampling instant, the QP problem is solved using the current state estimate $X_e[k]$. Only the first optimal control increment $\Delta u^*[k]$ is applied to the system, and the optimization is repeated at the next sampling time following the receding horizon principle.

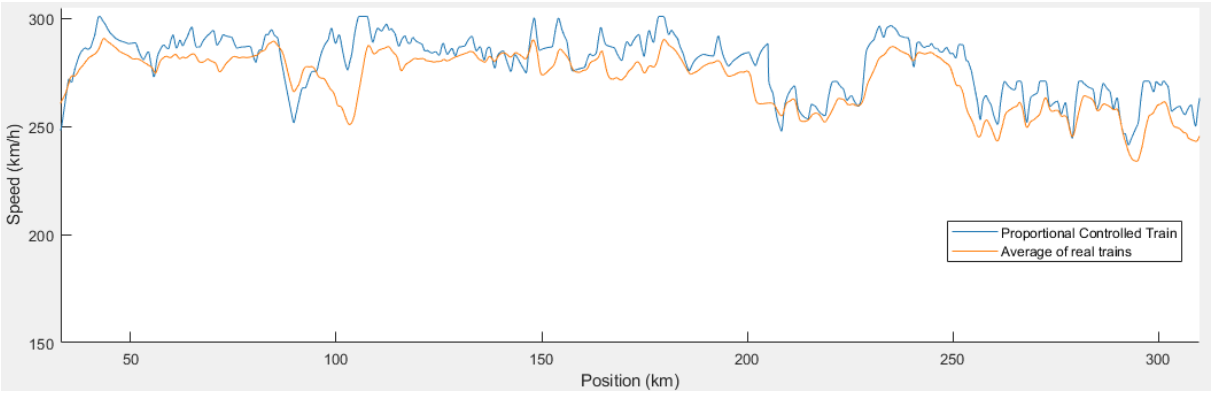
5.3 Simulation Results

Finally, the simulation results are presented in this section. First, model validation results are presented, including a preliminary comparison between real data and simulation results, and followed by the capacity gain assessment and the disturbance reaction analysis.

5.3.1 Model validation

To validate the models, several tests were conducted. First, a simple proportional-integral (PI) controller was proposed as an operator, taking as input the difference between the actual and the permitted speed. The overall behavior of the train along the line was then observed. Figure 13 presents a comparison between this mode of operation and the average behavior recorded in real data. In this scenario, the reference input was the speed limit, so it was expected that the train would operate closer to the limit than the average of real operators. Despite the inherent differences between a human operator and a PI controller, the general trend along the line was captured in both cases, indicating that the railway model is representative.

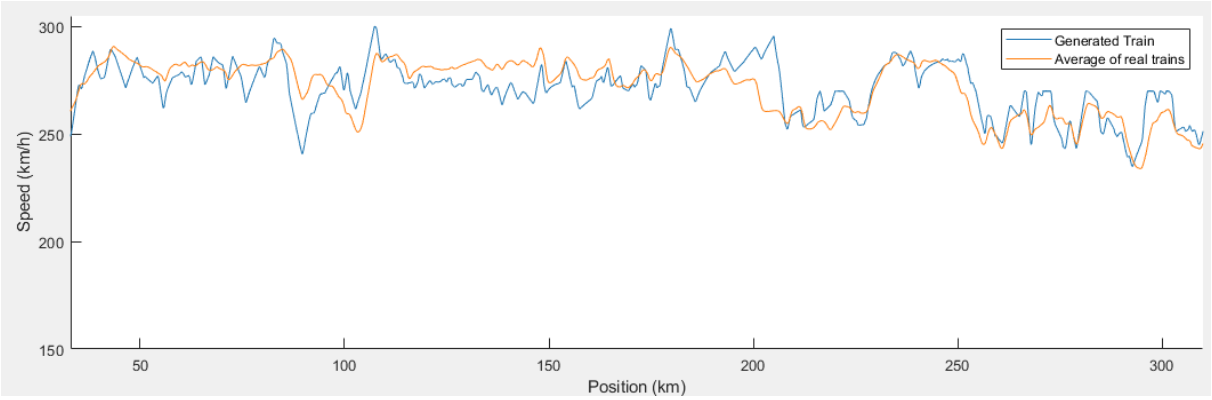
Figure 13 – Comparison results between a PI controller and the average of real operators



Later, to validate the operator generation method, a comparison was performed between the generated operators and the average behavior observed in real data. The results for a specific operator are presented in Fig. 14. This figure illustrates that the

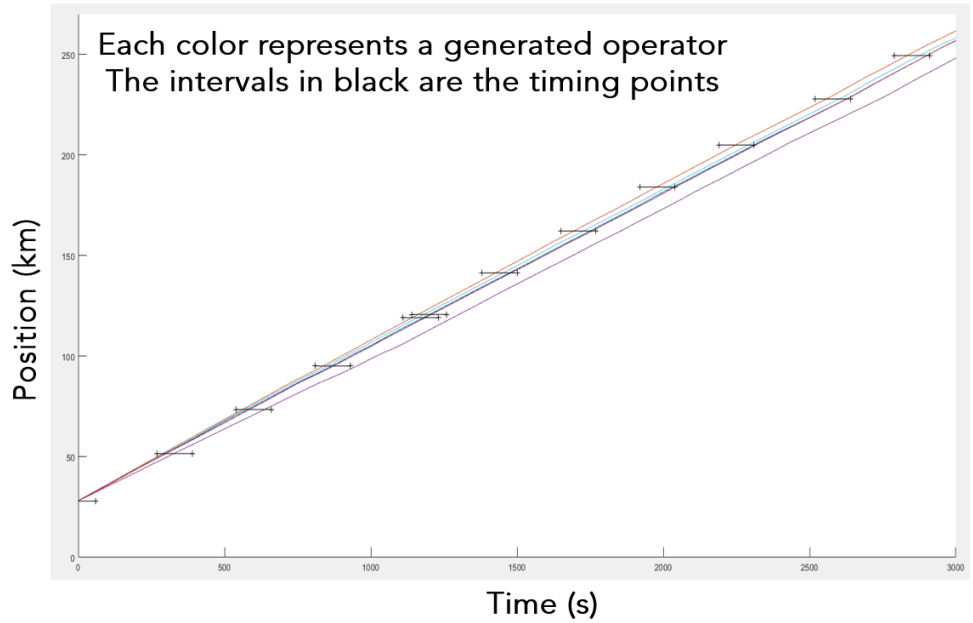
generated operator maintains speed more closely to the average during steady-speed phases. However, in situations involving speed reduction, the operator behaves more aggressively than the real-world average, as it tends to brake and accelerate more intensely than typical human operators.

Figure 14 – Comparison results between a generated operator and the average of real operators



Another validation test involved assessing compliance with timing points. Figure 15 shows the evaluation of the generated drivers in terms of their ability to keep the mission within the designated timing points. Operators that were consistently too slow or too fast, failing to remain within the timetable under nominal operating conditions, were discarded. The remaining operators, which complied with the timing point intervals, were further characterized as faster or slower than the average. In this context, the average operator would pass precisely at the center of the interval, while the others were allowed to vary within the timing window.

Figure 15 – Analysis of timetable compliance for generated operators



5.3.2 Capacity gain assessment

To assess the capacity gain, a two-train following scenario was proposed, to study the possible reduction of the interval between the trains. This scenario considers two trains operating under the same mission and timetable, only separated by a delay in the departure time. While both trains aim to follow the same overall timetable and mission objectives, their driving behavior may vary independently, reflecting differences in operator style or response. The baseline interval considered is 270 seconds, corresponding to a capacity of 13 trains per hour, as referenced in (SNCF Réseau, 2024), and observed in current timetables where no departures occur with intervals shorter than four minutes.

A train is said to operate in an unconstrained regime when it is able to follow its intended speed profile without needing to decelerate to maintain the minimum safety distance enforced by the EVC. In ERTMS Level 2, the most commonly adopted safety parameter between successive trains corresponds to seven track sections, which corresponds to an approximate physical distance of 17 km. Since the physical modeling focused on the LGV+, the analysis is carried out only along the high-speed line section - between its defined entry and exit points - thus excluding the initial acceleration phase after departure and the final deceleration phase before arrival.

The objective of this scenario is therefore to determine the shortest possible departure interval that still allows the second train to operate unconstrained. By progressively reducing the departure separation and analyzing when the following train begins to experience speed constraints due to safety distance limitations, the minimum headway ensuring unconstrained operation can be identified.

5.3.2.1 Manual Operation

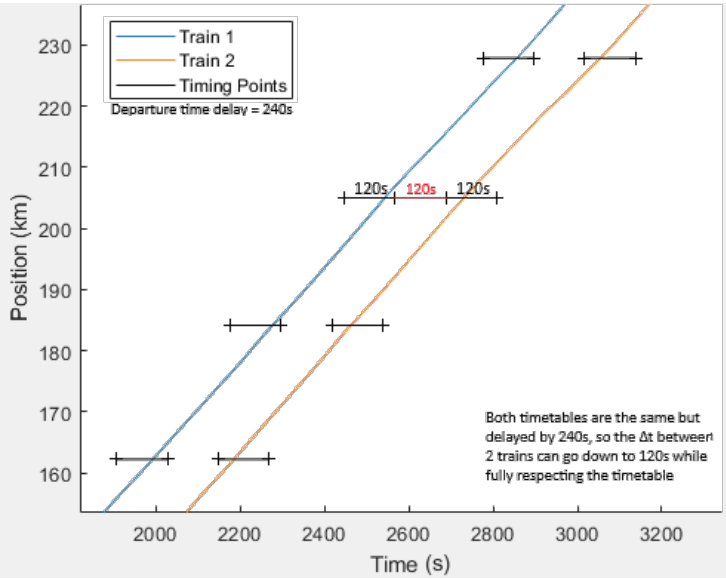
For manual operation, two different scenarios were evaluated. In the first scenario, both trains are operated by different generated drivers with similar operating profiles, aligned with the average behavior observed across all operators. In contrast, the second scenario represents a worst-case operational combination: the leading train is driven by an operator at the lower limit of the timetable (slightly slower), while the following train is driven by an operator at the upper limit (tending to run ahead of time). Even though both trains formally respect their timetables, their interaction reveals that the second train is forced to slow down to maintain the safety distance between the trains, even when their departure has a 270s interval, without proposing any reduction. In this case, the objective was to progressively increase the departure interval until the second train is able to run unconstrained.

To illustrate the worst-case scenario described above, consider the example shown in Fig. 16. If both trains depart 240 s apart, the timetable of the second train is

identical to that of the first one, except that the center of the interval of each timing point is shifted by 240 s. Since each timing point corresponds to a time window — typically two minutes wide — the actual gap between the end of the time window of the first train and the beginning of the corresponding window for the second train can be drastically reduced. In the example, it results in only a 120s gap, which translates into a distance smaller than the standard safety spacing.

As a consequence, the fastest operator who still respects the timetable, when following the slowest one, cannot run freely at all times. Instead, the operator is forced to reduce speed in order to maintain the required safety distance.

Figure 16 – Graphic representation of how the interval between two trains can be drastically reduced by two operators that are on the edges of their own timetables

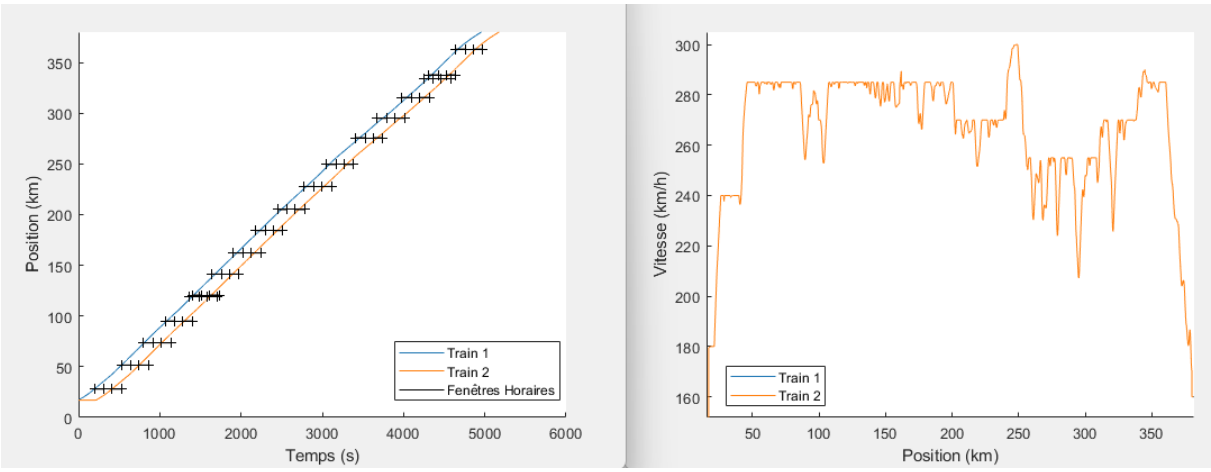


This analysis shows that a 4-minute departure interval is not operationally stable under manual operation. Any proposal to reduce this interval must address this worst-case scenario, in which this proposed interval is already below the minimum unconstrained headway for two manually operated trains.

5.3.2.2 ATO operation

For ATO operation, the two-train following scenario is still the same as previously described. The difference is that now both trains are assumed to follow the optimal speed profile perfectly when possible. This optimal profile is computed by an algorithm developed by the company and, in a real-case scenario, would serve as the reference input for a control system. In this scenario, the trains followed the pre-calculated command profile exactly, deviating from it only in case of interventions from the EVC, when a speed reduction becomes necessary due to an unsafe distance between the two trains.

Figure 17 – Simulation results for a 216s headway.
Left: time–position diagram. Right: speed–position diagram.



In Fig. 17, the left panel presents a time–position diagram showing that both ATO-operated trains respect their scheduled timings. The right panel displays a speed–position diagram in which the two speed profiles overlap perfectly, indicating that both trains followed the same optimal profile and remained unconstrained throughout the run.

The figure shows the simulation results for an interval of 216 seconds, identified as the minimum interval for the two-train following scenario in ATO operation, that will be presented in section 5.3.2.3. This value can also be approximated analytically: assuming an average speed of 285 km/h, a 216-second interval corresponds to a separation of approximately 17 km, matching the commonly adopted safety distance. Other simulations with different intervals are presented on the referenced sections.

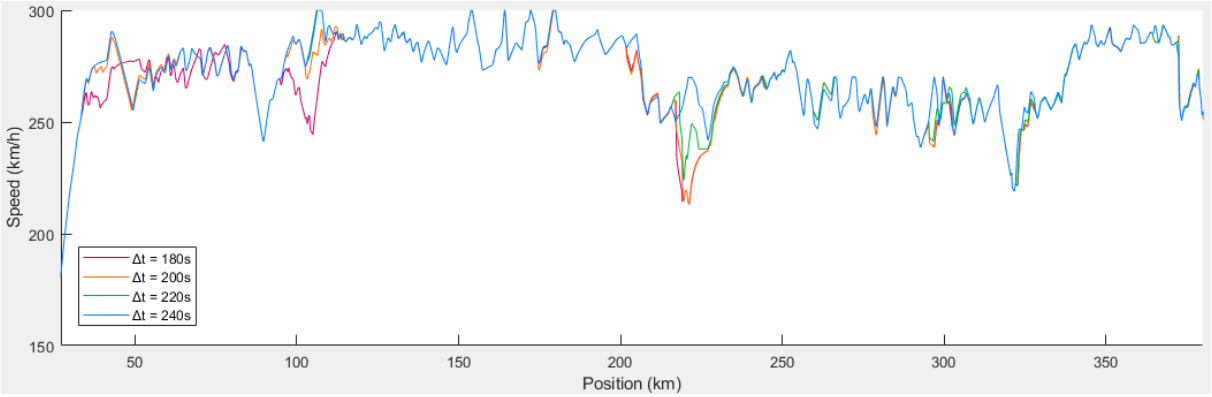
5.3.2.3 Capacity Gain Results

To identify the limiting headway for each of the three scenarios, several departure intervals were tested. For both the average operators and for ATO, a reference unconstrained profile was initially set at a 240s (4min) headway and then reduced in steps of 20s per test, down to 180s. This procedure allows the study to determine the 20s interval in which the optimal headway lies - between the smallest headway that still allows the second train to follow the reference profile and the largest headway where it does not. A finer-resolution sweep was then performed on the identified intervals to obtain the results presented in Table 1. For the worst-case scenario, proposing a significant difference between operators, the same methodology was applied, but since the 240s interval already constrained the second train, the tests were conducted by increasing the headway in 20s increments up to 300s.

For the two-train following scenario using the two manual operators closest to the average (Fig. 18), the minimum headway lies between 240s and 220s, as differences between their respective speed profiles already appear within this range. Further

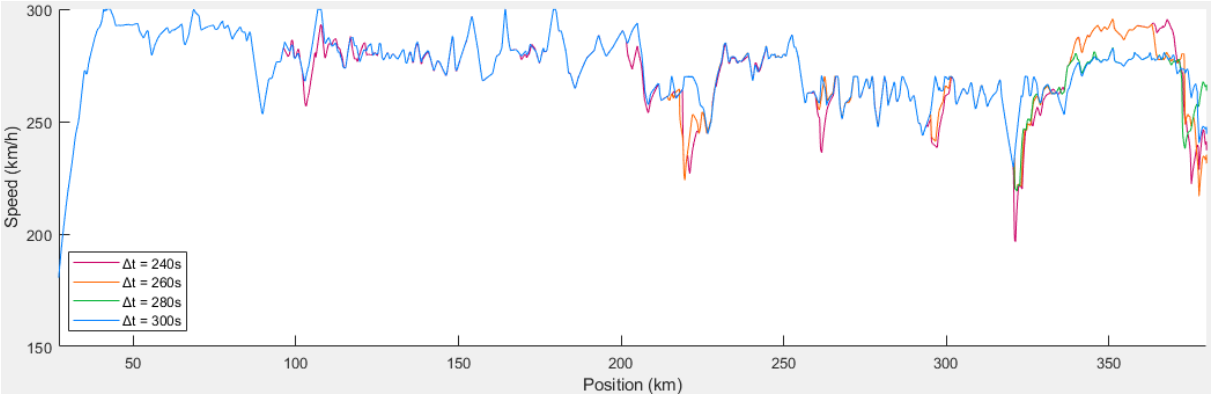
testing identified the smallest unconstrained headway on this case to be approximately 230s. This headway, however, is strongly dependent on which 2 operators are chosen - meaning that more or less aggressive operators can have different values.

Figure 18 – Simulation results comparing different headways for the average generated operators scenario



Now, for the worst-case manual scenario (Fig. 19), the minimum headway is between 300s and 280s. The refined assessment found a limiting interval around 288s.

Figure 19 – Simulation results comparing different headways for the worst-case generated operators scenario



Finally, for the ATO-operated trains (Fig. 20), the relevant interval was identified between 220s and 200s. Combined with the results shown in Fig. 17, this confirms the 216s headway as the limit. The combined results for headway and capacity are presented in Table 1. The data show that ATO operation achieves both a lower headway and a higher line capacity, and is the only scenario capable of exceeding the target of 16 trains/h planned for 2030 (SNCF Réseau, 2024). The main factors contributing to this improvement are the suppression of operator variability and human reaction times. These effects allow the train to run unconstrained for longer before any intervention is required, as the reaction time of the ATO is shorter, and they ensure a more predictable train behavior, thus reducing the propagation of potential instabilities along the line.

Figure 20 – Simulation results comparing different headways for the optimal ATO profile following scenario

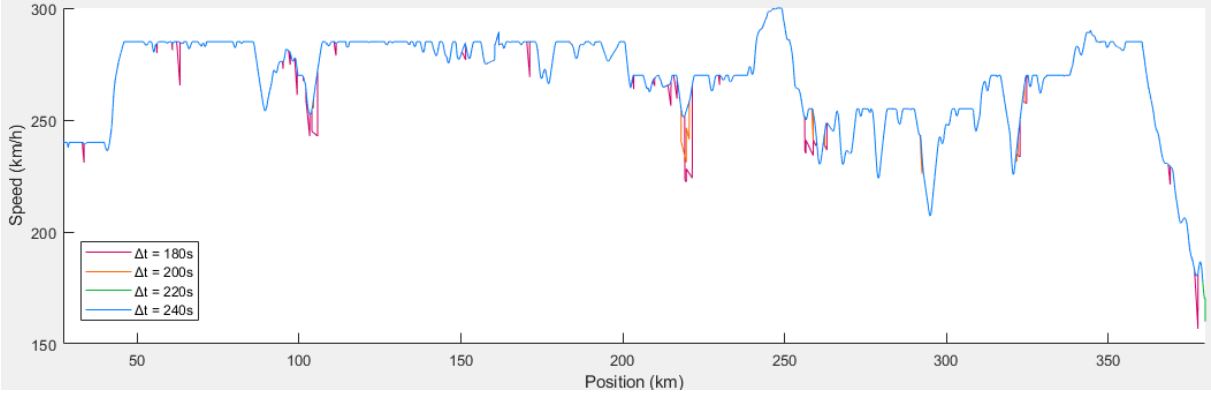


Table 1 – Interval limits on the 2-train following scenario

Mode of operation	**Limit interval (s)**	**Interval evolution (%)**	**Limit capacity (trains/h)**	**Capacity gain (%)**
Current situation (SNCF Réseau, 2024)	270	-	13.00	-
Average generated operators	230	-15	15.65	+20
Worst-case generated operators	288	+6	12.50	-4
Optimal ATO profile	216	-20	16.67	+28
2030 objective (SNCF Réseau, 2024)	225	-	16.00	-

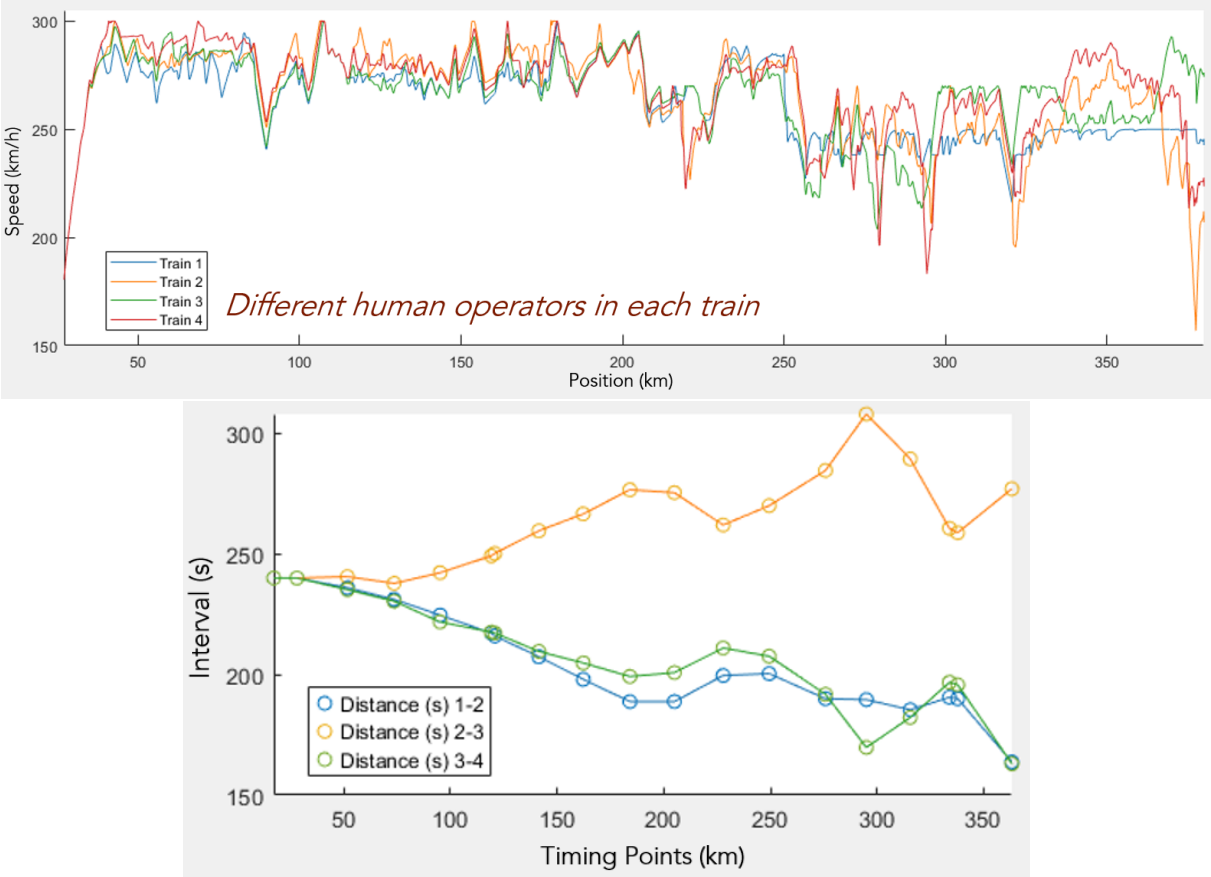
5.3.3 Delay recovery scenarios

Another relevant scenario in which ATO contributes to stabilizing operations is when the line is not running under nominal conditions - typically because of a disturbance -, resulting in delays for the trains in service.

The disturbances can have different natures, for example they can happen on a specific train, forcing the others behind it to reduce their speed, or be a local disturbance - such a temporary speed limit - on a certain section of the track. For this proposed scenario, the disturbance proposed was a technical problem with one train, that had a traction issue and its speed was limited to 250 km/h. The 3 trains following it, initially departing at a 240s interval from each other, were affected in different ways, as shown on Fig. 21. Different types of disturbances may yield different scenarios and would require separate analysis.

As seen on Fig. 21 results, the way each train reacts to the disturbance depends

Figure 21 – Speed–position diagrams (top) & evolution of the time gap (bottom) for a four-train following scenario, in which the first train is subject to speed restrictions beginning at the 250-km mark



heavily on the way the operator behaves and how far the train is positioned within its time slot. This brings back the observations made when discussing the capacity gains, in section 5.3.2, where even in nominal situations a train that was running on time and respecting its own schedule could still disrupt the train behind it, despite the follower also respecting their schedule. The same impact is observed on disturbed scenarios. For example, from the Fig. 21, the interaction between the first and second trains is that the second one, faster than the first, is constantly approaching it even before the technical issues, that prevent the first train from operating at full speed. The speed reduction intensifies the approach and leads the follower to alternate between normal operation and braking to keep its safety distance. However, as the third train has an operator that follows the time slot closer to the lower end of the dispersion (slower than the operator of the second train), the braking phases still exist, but are less intense than the ones from the second train, directly in front of it. However, the braking propagates from the third to the fourth train in a higher intensity, showing that the train's position inside its time slot will be important to define the moment where the disturbance is propagated from a train to another.

In ATO operation, even under disturbed conditions, the human factor responsible for train-to-train dispersion is not present, leading to a more uniform and less perturbed traffic flow. However, in situations with certain disturbances, such as isolated problems on individual trains, the standalone ATO is often not enough. In disturbance scenarios such as this one, with one train slowing down and affecting its followers, a standalone ATO won't solve the situation: it will only detect the slower train when closing the gap, brake to keep the safety distance, and then attempt to recover a delay that is rarely recoverable, since overtaking is generally not possible and the follower must eventually brake once it approaches too closely.

For this case, and to find a better operational gain under such disturbances, a connected ATO strategy should be considered. By exchanging information between trains, the system can compute an optimized solution that minimizes delay while accounting for energy consumption and downstream effects on other trains. A fair comparison to a connected ATO in a manual-driving context is a Connected Driver Advisory System (C-DAS), which provides operators with real-time information from other trains and therefore represents another potential approach to improve operational efficiency when facing disturbances.

5.3.4 Speed-tracking MPC implementation results

This section presents and discusses the closed-loop simulation results obtained with the speed-tracking Model Predictive Controller (MPC) developed in Section 5.2.4.1. The objective of these simulations is to demonstrate that the pre-computed energy-optimal speed profile, previously assumed as the ideal behavior for Autonomous Train Operation (ATO), can be effectively followed in a realistic closed-loop framework using a real-time predictive controller.

Simulation setup and MPC parameters

The MPC was implemented using the linearized train dynamics and executed over the entire route. At each sampling instant, the controller solved a constrained quadratic programming problem to compute the optimal control increment that minimizes the speed tracking error while respecting physical and operational constraints. Thus, the calculated control input was applied to the non-linear model of the system.

The main tuning parameters used in the presented simulations were:

- Prediction horizon: N_p = 60 steps;
- Control horizon: N_c = 15 steps;
- Speed tracking weight: Q = diag$(0, 1, 0)$ per step;
- Control change penalty: $R = 10\, I$.

The prediction and control horizons were selected as $N_p = 60$ and $N_c = 15$, respectively, corresponding to a prediction window of 12s and a control decision window of 3s, given the sampling time of $T_s = 0.2$s. This choice represents a practical trade-off between computational tractability and sufficient foresight for effective speed regulation. With a 12s prediction horizon, and considering a train operating at the maximum permitted speed of 300 km/h, the controller accounts for approximately 1 km ahead of the train when computing the control input.

A longer prediction horizon was adopted to allow the controller to anticipate upcoming speed variations, gradients, and infrastructure constraints with adequate temporal preview, which is particularly relevant for railway applications characterized by slow system dynamics and long stopping distances. At the same time, a shorter control horizon was chosen to limit the number of optimization variables in the quadratic program, significantly reducing computation time and ensuring real-time feasibility of the MPC implementation.

Figure 22 – Speed–position diagram of the MPC simulation and reference speed profile

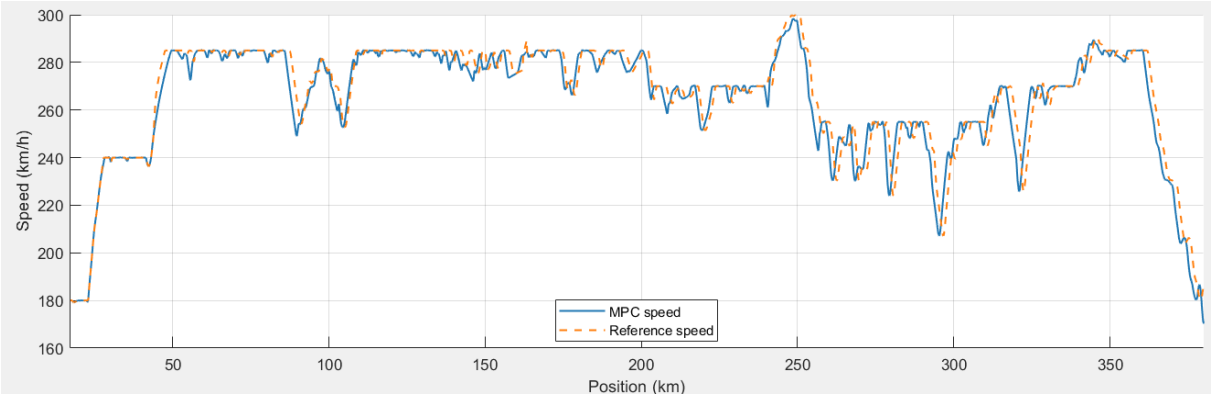


Figure 22 shows the simulated train speed as a function of position along with the pre-calculated reference speed profile. The results are presented from km 17 to km 380, corresponding to the section in which the train enters and exits the high-speed line and operates predominantly in cruise conditions. The results demonstrate that the MPC is capable of closely following the desired speed profile while respecting all operational constraints.

Minor deviations from the reference are observed, particularly in transition regions between acceleration and coasting or between cruising and braking. These discrepancies are consistent with the finite prediction horizon and the real-time nature of the control strategy, which lacks perfect foresight of future track conditions beyond the prediction window.

Quantitatively, the closed-loop tracking performance was evaluated using standard metrics. Let $v[k]$ denote the simulated train speed and $v_{\text{ref}}[k]$ the reference speed at time step k, with N being the total number of simulation steps. The considered performance indices were:

- Root Mean Square Error (RMSE): 6.45 km/h ($\approx$ 1.79 m/s),

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(v[k] - v_{\text{ref}}[k]\right)^2}, \tag{39}$$

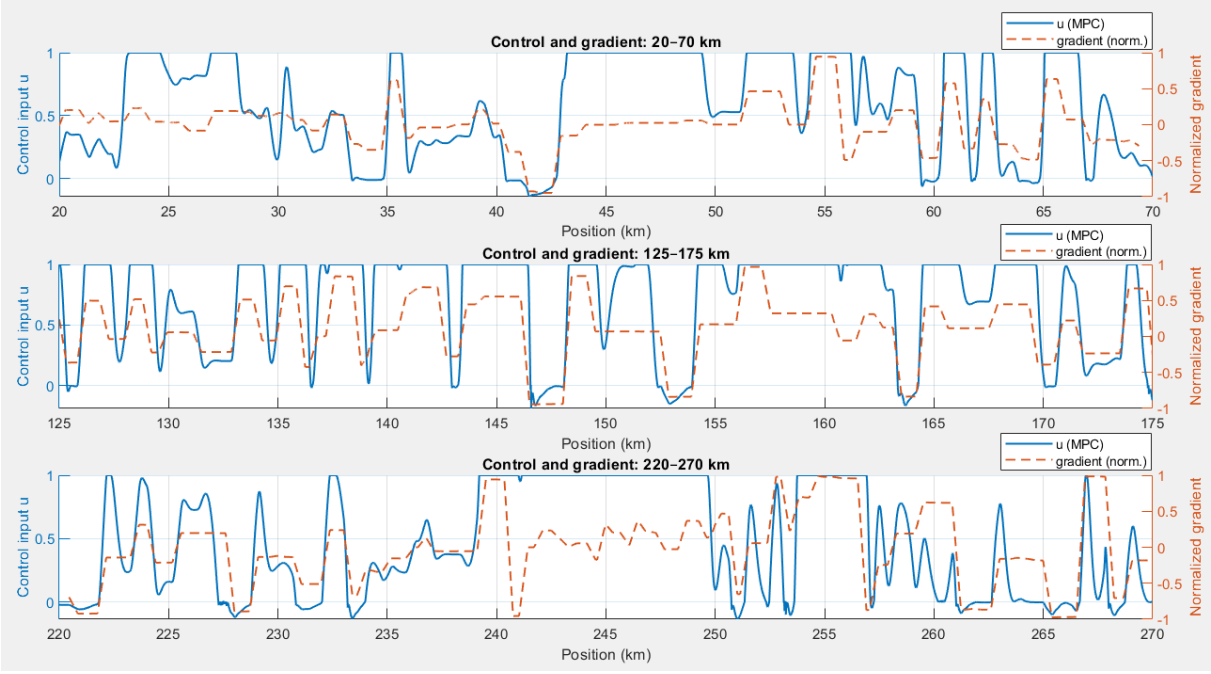
- Mean Absolute Percentage Error (MAPE): 1.62%.

$$\text{MAPE} = \frac{100}{N}\sum_{k=1}^{N}\left|\frac{v[k] - v_{\text{ref}}[k]}{v_{\text{ref}}[k]}\right|. \tag{40}$$

These values indicate high tracking accuracy, with the train remaining, on average, very close to the reference speed profile throughout the route.

Moving to the control input, it reveals a trade-off between accurate speed tracking and energy-efficient behavior. In several sections, the MPC alternates braking and traction, particularly when sudden speed changes are required to meet the constraints. As a result, the MPC exhibits more reactive traction and braking behavior, achieving superior speed tracking at the expense of energy optimality and increased actuator activity.

Figure 23 – Control Input of the MPC simulation and gradient for selected sections



To observe the control input, selected route segments were analyzed in detail by plotting the control input alongside the normalized track gradient (Figure 23). These zoomed-in views highlight the relationship between terrain profile and control decisions. The first section is the speed ramp-up, when the train accelerates to reach its cruise speed, while the other two sections were selected to show the behavior of the train over varying external conditions.

The results indicate that in uphill sections (positive gradient), the MPC tends to increase traction to maintain the reference speed, while in downhill sections (negative gradient), the controller often reduces traction or enters coasting mode. Sudden gradient changes sometimes trigger corrective braking actions, particularly when they coincide with speed restriction zones.

This analysis suggests that, although the MPC does not explicitly optimize energy or use gradient preview in its cost function, its behavior is indirectly influenced by track topography through the vehicle dynamics and speed reference. This influence originates from the gradient related parameters in the state-space, along with the pre-calculated speed profile, which already accounts for track gradients and energy consumption.

Overall, the results confirm that the proposed speed-tracking MPC formulation can effectively reproduce the desired ATO speed profile in closed loop, validating its feasibility as a real-time control strategy for automated train operation.

However, there is clear potential to improve the operational efficiency of the current MPC formulation. Future developments could include:

- Further tuning of MPC parameters: A more systematic tuning of the prediction and control horizons (N_p and N_c), as well as the weighting matrices Q and R, could improve the balance between tracking performance, computational effort, and control behavior. Different sets of parameters may allow better performance of the controller.
- Asymmetric control penalization: A variable control weighting matrix R that increases the penalization of braking actions ($u < 0$) could encourage longer coasting periods and reduce unnecessary deceleration. The use of coasting ($u = 0$) can help regulating speed while minimizing energy consumption.
- Smoothness penalization: Additional terms or fine-tuning of parameters in the cost function penalizing acceleration or jerk could promote more gradual speed changes and reduce corrective braking.

These propositions would help to improve the controller to an energy-aware MPC while maintaining its robustness and constraint-satisfying speed tracking in real time.

6 CONCLUSION

This work addressed the challenge of limited capacity and operational variability on high-speed railway corridors, focusing on the Paris–Lyon line operated under ERTMS Level 2. The objective was to evaluate whether the implementation of Autonomous Train Operation (ATO) at Grade of Automation 2 could improve headway stability and increase line capacity when compared to manual operation.

The main contribution of this work is the development of an integrated and modular simulation framework enabling the quantitative evaluation of ATO deployment under ERTMS Level 2 conditions.

A modular and parametrizable simulation framework was developed in MATLAB/Simulink, integrating longitudinal train dynamics, a human operator behavioral model derived from real driving data, ERTMS supervision through the European Vital Computer (EVC), and multi-train traffic interaction. This integrated architecture enabled a consistent comparison between manual driving and automatic operation under identical operational conditions.

The results demonstrate that ATO significantly reduces headway variability and enables a reduction of departure intervals from 270 s to 216 s. This corresponds to an increase in theoretical line capacity from 13 to approximately 16.67 trains per hour, exceeding the 16 trains/h target defined for 2030 by the SNCF (SNCF Réseau, 2024). These results indicate that, within the simulated conditions, capacity improvements can be achieved through operational optimization without requiring additional infrastructure investments.

The project successfully fulfilled its three main objectives:

1. the development of a flexible train circulation model,
2. the implementation and comparison of manual and automatic driving modes, and
3. the quantitative evaluation of operational performance metrics.

In addition, the validation of the ideal ATO strategy through a Model Predictive Control (MPC) implementation strengthened the robustness of the proposed approach and demonstrated the feasibility of real-time predictive control for railway applications.

Still, several limitations must be acknowledged. The simulations were conducted under a specific set of operating conditions and relied on modeling assumptions that may not capture the full complexity of real-world railway systems. The standalone ATO architecture exhibited limited disturbance recovery capability due to the absence of inter-train communication. Furthermore, although representative, the human operator model could be refined to better capture behavioral variability, potentially through data-driven or machine learning approaches.

Future developments may include the integration of energy consumption as an explicit optimization criterion within the MPC formulation, the extension of the framework to additional lines and operational contexts (including station stops and denser traffic scenarios), and the implementation of communication-enabled architectures such as connected ATO or C-DAS systems to enhance disturbance management and network-wide optimization.

Beyond its technical contributions, this work provides a validated simulation framework that can support decision-making regarding ATO deployment under ERTMS standards. The demonstrated improvements in regularity, capacity, and operational smoothness suggest that automation technologies constitute a viable path toward modernizing high-speed railway systems while contributing to long-term operational efficiency and sustainability.

In conclusion, this project illustrates how control engineering principles, such as dynamic modeling, predictive control, and system-level simulation, can be applied to a complex industrial problem, bridging theoretical knowledge and real-world railway operation. The results indicate that automation represents a technically feasible and operationally effective strategy for increasing capacity on high-speed railway corridors without additional infrastructure expansion.

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