Driving the future of autonomous train operation: The R2DATO Project

Roger Idrovo, Paul Zabalegui, Sergio Arana, Jaizki Mendizabal; CEIT, San Sebastián, Guipúzcoa, Spain.

Introduction

The implementation of fully automated train operation (ATO) up to unattended operation in Grade of Automation 4 (GoA4) represents a significant milestone in the railway industry. The implementation of Automated Train Operation (up to GoA4) will undoubtedly yield multiple benefits, including:

- A reduction in environmental impact through the decrease in energy consumption.
- An enhancement of public transport attractiveness through the decrease in operating costs, enabling public authorities to invest in better services.
- An improvement in the quality of service, as shorter and more predictable journey times lead to increased punctuality and a higher quality of service, thereby attracting more passengers to use public transport.

These benefits are in line with the vision of a fully automated rail system that enhances interoperability based on the European Train Control System (ETCS) specifications. In this work, two key areas relevant to Automatic Train Operation (ATO) up to GoA4 are addressed: the novel reference architecture for GoA3/4 systems derived from the X2Rail-4 project, and the ATO driving functions, including intelligent algorithms designed to optimize speed profiles and automatic tracking control.

Novel reference architecture for GoA 3/4 automation level

The R2DATO project [1], which is grounded in the X2Rail-4 project [2] and relevant standards such as the Technical Specification for Interoperability – Control Command and Signalling (TSI – CCS) [3], is focused on developing innovative solutions that facilitate the rapid and cost-effective implementation and migration of digital and automatic train operation systems. Additionally, the R2DATO project [1] is currently updating and developing system requirements for ATO up to GoA 4, including the novel reference architecture that was originally established in the X2Rail-4 project [2]. The framework of this novel reference architecture is illustrated in Figure 1 and represents an advancement from the traditional reference architecture described in the ERTMS/ATO System Requirement Specification, SUBSET-125 [4].
The framework of the novel reference architecture encompasses both trackside and onboard systems. The upper part of the framework is focused on the trackside components, which includes the Traffic Management, Train Management, Train Control, Digital Map (DM), Operational Execution (OE), Mission Data (MD), and Train Data (TD). On the other hand, the lower part of the framework is dedicated to the onboard components, which includes the Train Protection, Localization (LOC), Train Control and Monitoring System (TCMS), and four novel GoA 3/4 components, namely Automatic Driving Module (ADM), Automatic Processing Module (APM), Repository (REP), and Perception (PER).

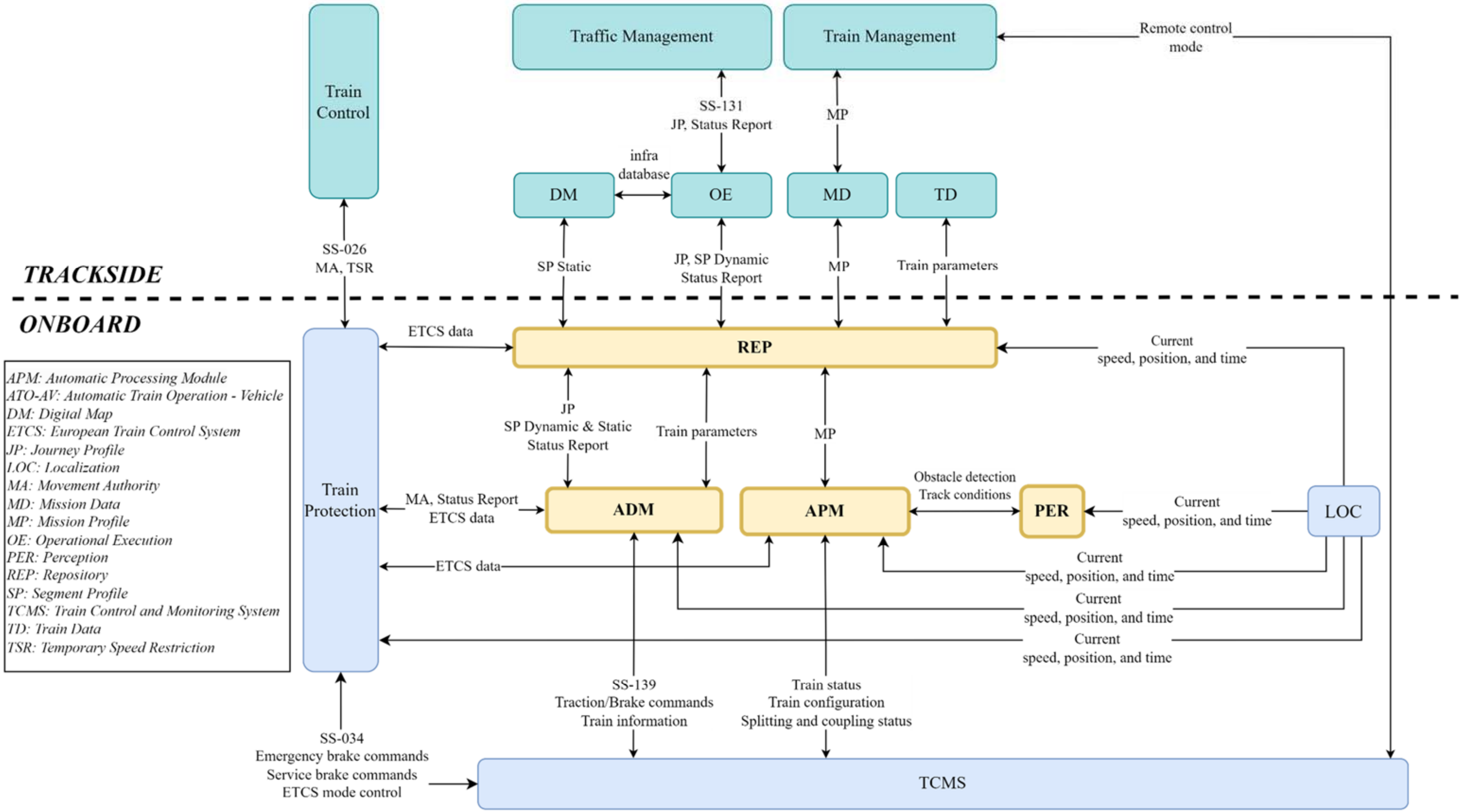

Figure 1: Framework of the novel reference architecture for GoA 3/4 systems based on X2Rail-4 project [2].

GoA 3/4 components

The aforementioned reference architecture is composed of several components, including four GoA 3/4 components. The remaining components are detailed in the Deliverable D5.1 WP5 GoA3/4 Specification document from the X2Rail-4 Project [2].

1. **Perception (PER):** The PER module is considered as the “eyes” of the driver in GoA3/4 systems, comprising a group of onboard sensors with the aim to evaluate the Physical Railway Environment and enhance the perception of the driver, encompassing not only visual sensing but also other factors that contribute to safety and dependability in operations. The perception of the external environment involves the detection and recognition of static or dynamic objects of various types that may impact the operation of the train, such as a fallen tree on the tracks or a road vehicle on an unprotected level crossing.
2. **Automatic Processing Module (APM):** The APM module is regarded as the “brain” of the driver in GoA3/4 systems, as it is responsible for emulating the responsibilities of the driver and train attendant in responding to incidents. This onboard module oversees the execution of missions, safe reflexive actions, evaluated reactions, and safety procedures that occur during the mission, including both train and track incidents.
3. **Repository (REP):** This onboard module is designed to collect, check and filter data received from various trackside modules such as DM (segment profile static data), OE (journey profile data, segment profile dynamic data), MD (mission profile data), and TD (train data set), according to the requirements of the on-board components, and subsequently transmit it via the relevant interfaces.
4. **Automatic Driving Module (ADM):** This module is concerned as the “hearth” of the train operation since GoA2 and is responsible for execute the driving functions which allow to driving the train automatically. According to the SUBSET-125 [4], the ATO driving functions are as follows:

   - **Supervised Speed Envelope Management (SSEM):** This function computes the maximum speed that the train can be achieved without ETCS intervention.
   - **Automatic Train Stopping Management (ATSM)**: This function indicates the speed profile to be used to stop the train accurately at the operational stopping point.
   - **Time Table Speed Management (TTSM):** This function takes into account the information from the Journey Profile (JP) and the Segment Profile (SP) to calculate the optimal speed profile to run the train in the most energy-efficient way while respecting the infrastructure constraints and timing points. Furthermore, the optimal speed profile should be continuously updated based on the current position and speed of the train.
   - **Traction/brake control:** This function is primarily responsible for the accurate and effective generation of ATO output commands to be used to follow the optimal speed curve calculated from TTSM, ATSM, and SSEM.

Smart algorithms for ATO driving functions.

As previously stated, the basic structure of ATO driving functions comprises two key components, which collaboratively fulfill the operational requirements of automation and efficiency [5]. These two components are:

- Speed profile optimization, which is typically formulated as an optimal control problem based on the train operation model and employs smart algorithms to determine the optimum speed profile.
- Automatic tracking control, which utilizes control methods to ensure that the train can track the optimal speed profile precisely and operate safely and smoothly.

Speed Profile Optimization Techniques

Upon examining the existing literature, various techniques have been identified for optimizing train speed profiles. These techniques include analytical approaches, numerical methods, and genetic algorithms.

1. *Analytical approaches:* The issue of determining the most efficient method for controlling the movement of a train was initially raised by Milroy [6], who obtained a basic velocity profile and suggested it as an optimal strategy by applying the analytical approach known as the Pontryagin maximum principle. Similarly, Asnis [7] examines the various types of optimal trajectories that satisfy the maximum principle. On the other hand, Howlett [8] used the Pontryagin maximum principle to discover the precise optimal strategy for achieving a minimum cost journey.
2. *Numerical methods:* This type of method has relatively fewer requirements for the objective function and can make a trade-off between optimization performance and computational time. Miyatake [9] introduced three numerical methods (dynamic programming, gradient method, and sequential quadratic problem) to solve the optimal control problem with constraints for finding energy-saving train speed profiles. On the other hand, the optimal control problem for minimizing energy consumption by a train, as proposed by Ko [10], has been numerically solved using Bellman's Dynamic Programming algorithm within an acceptable computational timeframe. This method can be applied to actual complicated running conditions. Similarly, Thorlund [11] introduced a novel dynamic programming approach to find optimized speed profiles that result in reduced energy consumption.
3. *Genetic algorithms:* Genetic algorithms (GA) have been effectively utilized in coasting control optimization to determine the optimal train trajectory [12]. In his work, Chang [13] proposed a GA for determining the number of coasting points. The results of this approach demonstrated promising performance in the trade-off between journey time and energy consumption. Similarly, Wong [14] applied a genetic solution to search for coasting points. The number of coasting points was dynamically allocated into the chromosomes, which enhanced the practical application of this approach. Söylemez [15] proposed a novel method that utilized artificial neural networks and genetic algorithms to optimize coasting points for trains.

Automatic Tracking Control Techniques

Upon generating the optimal speed profile, the subsequent step in train operation involves devising an effective and accurate method to control train movements, ensuring precise tracking to the speed profile and maintaining safety and smoothness. Literature review reveals several techniques for automatic tracking control, including PID controllers, sliding mode controllers, and adaptative control methods.

1. *PID controllers:* The most widely used train speed control method of ATO is the PID controller, which continuously calculates the error value between the measured train speed and recommended speed, and adjusts the control command to minimize the speed tracking error over time. The existing challenges in this kind of controller is how to determine the best PID coefficients considering that the parameters of train models are always affected by some external factors in daily operations, such as weather condition, normal deterioration and mechanical wear. These parameters variations will inevitably reduce the performance of PID controller if the PID coefficients are fixed.
   To solve this challenge, some studies are developed novel solutions. One of such is the combination of fuzzy control with PID control to provide advantages about the object description, fuzzy rules can be designed with prior knowledge of human drivers, and the parameters of PID controller could be adjusted dynamically so to improve the performance. Ke [16] determined the speed commands of the ATO system by manipulated by the fuzzy-PID gain scheduler under acceleration, deceleration and jerk restrictions. Similarly, Yang [17] proposed a fuzzy-PID solution to meet the performance demand of the freight train control.
2. *Sliding Mode Controllers:* These controllers are recognized for their high effectiveness in various practical systems, as numerous studies have demonstrated [18], [19], [20]. Incorporating an appropriate nonlinear sliding surface in sliding mode control (SMC) can ensure that the closed-loop system's state converges to a balanced point within a finite time frame [21]. Some studies focus on SMC solutions for automatic tracking control. Wu [22] focused on the control problem of precise and comfortable train operation through the use of adaptive terminal sliding mode control, introducing a novel terminal sliding surface to ensure stability and robustness. Conversely, Yao [23] applied robust adaptive sliding mode control strategies to study the position and velocity tracking control problem of trains.
3. *Adaptative Control Methods:* The controller in question is employed in high-speed applications where achieving train speed control presents a formidable challenge [5]. This is attributed to the intricate nature of the operation and the rapid dynamics of the train. In this regard, certain studies opt for the implementation of adaptive control techniques to manage the intricacy and uncertainty associated with train operation models. Yang [24] presented a mixed H_2/H_∞ controller, which is synthesized through the use of linear matrix inequalities to attain the objective of speed command tracking. Conversely, Chou [25] proposed an adaptive control system for heavy-haul train applications, which is adaptive to various optimization objectives, including energy consumption, velocity tracking, and in-train force.

Future works

Optimizing speed profiles and automatic tracking control are crucial tasks that guarantees efficient, dependable, and secure train operations. Traditional algorithms use kinematical equations to determine the train speed profile, which serves as the target of train control. However, these equations rely on assumptions made in empirical formulas, which can lead to potential errors [26]. With the advancement of artificial intelligence, various challenges and opportunities arise in the development of intelligent algorithms. The following highlights research works and emergent trends in speed profile generation and automatic tracking control.

Reinforcement learning aims to train a system to control a particular environment in order to maximize a numerical performance associated with a long-term objective. Unlike deep learning, reinforcement learning involves a trial-and-error process in which the agent learns to make decisions on its own without the assistance of a pre-existing dataset [27]. The application of artificial intelligence (AI) algorithms, particularly deep learning and reinforcement learning, has led to the development of AI algorithms to address the challenges of optimizing train speed profiles and automatic tracking control in various railway systems. To address the speed curve optimization problem for urban metro trains, Yin [28] proposed two intelligent train operation algorithms, one based on an expert system and the other on reinforcement learning (RL). In contrast, Ning [29] presented a novel train trajectory optimization approach for high-speed railways that utilizes the deep deterministic policy gradient (DDPG) method to generate optimal train trajectories through offline training based on the agent's interaction with the trajectory simulation environment. On the other hand, Chen [30] proposed an automatic driving control method for urban rail trains based on the Deep Q Network algorithm. Wang proposed a novel decision-making framework, which consists of two parts including a reference speed trajectory generator and a backstepping tracking controller. The speed trajectory generator is responsible for calculating the reference speed trajectory dynamically using hybrid deep learning structure. Based on the backstepping technique, the designed tracking controller takes the reference speed trajectory as the tracking target, and guarantees that the pair-wise distance between adjacent trains is stabilized to a given steady value within a safe range.

Conclusions

The current work highlights a novel reference architecture for GoA3/4 from the X2Rail-4 Project, which comprises four innovative components such as Repository (REP), Perception (PER), Automatic Processing Module (APM), and Automatic Driving Module (ADM). The objective is to bring attention to the capabilities of ATO up to the GoA4 system requirements specification, a subject that has been comprehensively explored in recent years.

Furthermore, this work delved into the operational functions of ATO systems, with a particular focus on methods, approaches, and techniques for addressing train operation challenges. Typically, these challenges are addressed by implementing optimized speed profiles and train speed controllers. The incorporation of smart algorithms, particularly those utilizing artificial intelligence and machine learning, presents a substantial opportunity to improve the accuracy, efficiency, and safety of train operations. Through the continuous refinement of these algorithms and the incorporation of real-time data and adaptive control techniques, the railway industry can attain unparalleled levels of automation and dependability, ultimately contributing to a more sustainable and efficient transportation system.

References

[1] "Europe's Rail Flagship Project 2 - Rail to Digital automated up to autonomous train operation | FP2 - R2DATO Project | HORIZON," CORDIS | European Commission. Accessed: Jul. 14, 2024. [Online]. Available: https://cordis.europa.eu/project/id/101102001

[2] "Advanced signalling and automation system - Completion of activities for enhanced automation systems, train integrity, traffic management evolution and smart object controllers | X2Rail-4 Project | H2020," CORDIS | European Commission. Accessed: Jul. 14, 2024. [Online]. Available: https://cordis.europa.eu/project/id/881806

[3] "1. CCS TSI Appendix A – Mandatory specifications (ETCS B4 R1, RMR: GSM-R B1 MR1 + FRMCS B0, ATO B1 R1) | European Union Agency for Railways." Accessed: Jul. 14, 2024. [Online]. Available: https://www.era.europa.eu/era-folder/1-ccs-tsi-appendix-mandatory-specifications-etcs-b4-r1-rmr-gsm-r-b1-mr1-frmcs-b0-ato-b1

[4] "ERTMS/ATO System Requirement Specification: SUBSET-125." Accessed: Jul. 15, 2024. [Online]. Available: https://www.era.europa.eu/era-folder/1-ccs-tsi-appendix-mandatory-specifications-etcs-b4-r1-rmr-gsm-r-b1-mr1-frmcs-b0-ato-b1

[5] J. Yin, T. Tang, L. Yang, J. Xun, Y. Huang, and Z. Gao, "Research and development of automatic train operation for railway transportation systems: A survey," *Transportation Research Part C: Emerging Technologies*, vol. 85, pp. 548–572, Dec. 2017, doi: 10.1016/j.trc.2017.09.009.

[6] Ian P. Milroy, "Aspects of automatic train control," 1980. [Online]. Available: https://repository.lboro.ac.uk/articles/thesis/Aspects_of_automatic_train_control/9537395

[7] I. A. Asnis, A. V. Dmitruk, and N. P. Osmolovskii, "Solution of the problem of the energetically optimal control of the motion of a train by the maximum principle," *USSR Computational Mathematics and Mathematical Physics*, vol. 25, no. 6, pp. 37–44, Jan. 1985, doi: 10.1016/0041-5553(85)90006-0.

[8] P. Howlett, "An optimal strategy for the control of a train," *J. Aust. Math. Soc. Series B, Appl. Math*, vol. 31, no. 4, pp. 454–471, Apr. 1990, doi: 10.1017/S0334270000006780.

[9] M. Miyatake and H. Ko, "Optimization of Train Speed Profile for Minimum Energy Consumption," *IEEJ Transactions Elec Engng*, vol. 5, no. 3, pp. 263–269, May 2010, doi: 10.1002/tee.20528.

[10] KO, H, "Application of dynamic programming to optimization of running profile of a train," *Computers in Railways*, vol. 0, pp. 103–112, 2004.

[11] J. T. Haahr, D. Pisinger, and M. Sabbaghian, "A dynamic programming approach for optimizing train speed profiles with speed restrictions and passage points," *Transportation Research Part B: Methodological*, vol. 99, pp. 167–182, May 2017, doi: 10.1016/j.trb.2016.12.016.

[12] S. Lu, S. Hillmansen, T. K. Ho, and C. Roberts, "Single-Train Trajectory Optimization," *IEEE Trans. Intell. Transport. Syst.*, vol. 14, no. 2, pp. 743–750, Jun. 2013, doi: 10.1109/TITS.2012.2234118.

[13] C. S. Chang and S. S. Sim, "Optimising train movements through coast control using genetic algorithms," *IEE Proc., Electr. Power Appl.*, vol. 144, no. 1, p. 65, 1997, doi: 10.1049/ip-epa:19970797.

[14] K. K. Wong * and T. K. Ho, "Dynamic coast control of train movement with genetic algorithm," *International Journal of Systems Science*, vol. 35, no. 13–14, pp. 835–846, Oct. 2004, doi: 10.1080/00207720412331203633.

[15] M. T. Söylemez and S. Açıkbaş, "Coasting point optimisation for mass rail transit lines using artificial neural networks and genetic algorithms," *IET Electric Power Applications*, vol. 2, no. 3, pp. 172–182, May 2008, doi: 10.1049/iet-epa:20070381.

[16] B.-R. Ke, C.-L. Lin, and C.-W. Lai, "Optimization of train-speed trajectory and control for mass rapid transit systems," *Control Engineering Practice*, vol. 19, no. 7, pp. 675–687, Jul. 2011, doi: 10.1016/j.conengprac.2011.03.003.

[17] J. Yang, L. Jia, Y. Fu, and S. Lu, "Speed Tracking Based Energy-Efficient Freight Train Control Through Multi-Algorithms Combination," *IEEE Intell. Transport. Syst. Mag.*, vol. 9, no. 2, pp. 76–90, 2017, doi: 10.1109/MITS.2017.2666580.

[18] X. Guo, J. Wang, F. Liao, and R. S. H. Teo, "Distributed Adaptive Sliding Mode Control Strategy for Vehicle-Following Systems With Nonlinear Acceleration Uncertainties," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 981–991, Feb. 2017, doi: 10.1109/TVT.2016.2556938.

[19] K. Han, M. Choi, B. Lee, and S. B. Choi, "Development of a Traction Control System Using a Special Type of Sliding Mode Controller for Hybrid 4WD Vehicles," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 264–274, Jan. 2018, doi: 10.1109/TVT.2017.2752704.

[20] Man Zhihong, A. P. Paplinski, and H. R. Wu, “A robust MIMO terminal sliding mode control scheme for rigid robotic manipulators,” *IEEE Trans. Automat. Contr.*, vol. 39, no. 12, pp. 2464–2469, Dec. 1994, doi: 10.1109/9.362847.
[21] Y. Cao, Z.-C. Wang, F. Liu, P. Li, and G. Xie, “Bio-Inspired Speed Curve Optimization and Sliding Mode Tracking Control for Subway Trains,” *IEEE Trans. Veh. Technol.*, vol. 68, no. 7, pp. 6331–6342, Jul. 2019, doi: 10.1109/TVT.2019.2914936.
[22] P. Wu, Q.-Y. Wang, and X.-Y. Feng, “Automatic train operation based on adaptive terminal sliding mode control,” *Int. J. Autom. Comput.*, vol. 12, no. 2, pp. 142–148, Apr. 2015, doi: 10.1007/s11633-015-0877-y.
[23] X. Yao, J. H. Park, H. Dong, L. Guo, and X. Lin, “Robust Adaptive Nonsingular Terminal Sliding Mode Control for Automatic Train Operation,” *IEEE Trans. Syst. Man Cybern, Syst.*, vol. 49, no. 12, pp. 2406–2415, Dec. 2019, doi: 10.1109/TSMC.2018.2817616.
[24] C.-D. Yang and Y.-P. Sun, “Mixed H_2/H cruise controller design for high speed train,” *International Journal of Control*, vol. 74, no. 9, pp. 905–920, Jan. 2001, doi: 10.1080/00207170010038703.
[25] M. Chou and X. Xia, “Optimal cruise control of heavy-haul trains equipped with electronically controlled pneumatic brake systems,” *Control Engineering Practice*, vol. 15, no. 5, pp. 511–519, May 2007, doi: 10.1016/j.conengprac.2006.09.007.
[26] K. Huang, J. Wu, X. Yang, Z. Gao, F. Liu, and Y. Zhu, “Discrete Train Speed Profile Optimization for Urban Rail Transit: A Data-Driven Model and Integrated Algorithms Based on Machine Learning,” *Journal of Advanced Transportation*, vol. 2019, pp. 1–17, May 2019, doi: 10.1155/2019/7258986.
[27] Szepesvári Csaba, *Algorithms for reinforcement learning*. Springer nature, 2022.
[28] J. Yin, D. Chen, and L. Li, “Intelligent Train Operation Algorithms for Subway by Expert System and Reinforcement Learning,” *IEEE Trans. Intell. Transport. Syst.*, vol. 15, no. 6, pp. 2561–2571, Dec. 2014, doi: 10.1109/TITS.2014.2320757.
[29] L. Ning, M. Zhou, Z. Hou, R. M. P. Goverde, F.-Y. Wang, and H. Dong, “Deep Deterministic Policy Gradient for High-Speed Train Trajectory Optimization,” *IEEE Trans. Intell. Transport. Syst.*, vol. 23, no. 8, pp. 11562–11574, Aug. 2022, doi: 10.1109/TITS.2021.3105380.
[30] X. Chen, X. Guo, J. Meng, R. Xu, S. Li, and D. Li, “Research on ATO Control Method for Urban Rail Based on Deep Reinforcement Learning,” *IEEE Access*, vol. 11, pp. 5919–5928, 2023, doi: 10.1109/ACCESS.2023.3236413.

Authors

Roger Idrovo received his B.Sc. degree in Electrical Engineering from the ESPOL Polytechnic University, Ecuador in 2016, and the M.Sc. degree in Automatic Systems and Industrial Electronics Engineering from the Polytechnic University of Catalonia, Spain in 2021. He is currently pursuing the Ph.D. degree from Universidad de Navarra, Spain. He joined the CEIT-BRTA Research Centre, Spain in 2023, and he is currently a Researcher assistant within the Transport and Sustainable Mobility group. He is now actively participating in EU-Rail Projects, including R2DATO and MOTIONAL. His research interests include optimal control theory, speed profile optimization, and automatic train operation.

ridrovou@ceit.es

Paul Zabalegui received his PhD in applied engineering in 2022 and his M.Sc. degree in Telecommunications Engineering from Universidad de Navarra, Spain, in 2018, respectively. He joined the CEIT-BRTA Research Centre, Spain, in 2019, and he is currently a Researcher scientist within the Transport and Sustainable Mobility group. His research activity lies in the field of positioning and software development. He is the co-author of three software registers and the author or co-author of 8 articles in journals and international conferences. He is now actively participating in European-funded projects in Railway signaling and positioning topics.

pzabalegui@ceit.es

Sergio Arana earned his degree in Electronics and Control Engineering from Universidad de Navarra, Spain in 1999, followed by a Ph.D. in Engineering in 2003. From 1999 to 2020, he dedicated his efforts to the Microelectronics and Microsystems Department at CEIT-BRTA Research Centre, where he led the bioMEMS Group. In 2021, he transitioned to Sustainable Transportation and Mobility group. In addition to his research, he serves as an Associate Professor at the Universidad de Navarra, Tecnun. His extensive involvement in over 50 industrial and research projects has resulted in seven patents. As an author or co-author, he has contributed to more than 50 scientific and technical papers and participated in over 60 national and international conferences. He also lends his expertise as a referee for several international journals. In recognition of his significant contributions to the scientific activities of the city, he was honored as an ambassador of the city of San Sebastian in 2012.

sarana@ceit.es

Jaizki Mendizabal is a researcher at CEIT-BRTA Research Centre and a lecturer at the Universidad de Navarra, Tecnun. He received his MSc and PhD degrees in Electrical Engineering from Universidad de Navarra in 2000 and 2006 respectively. He joined Fraunhofer IIS-A (Germany) from 2000 to 2002 and SANYO Electric Ltd (Japan) from 2005 to 2006 as RFIC designer. He obtained his PhD in the field of RF design for GNSS systems. Currently, his research interests at CEIT-BRTA include GNSS, wireless communication automation and safety-critical systems for the railway industry. He has been engaged in the SIL4 design of a safety critical receiver for an ERTMS BTM for high speed, he was the project coordinator of the FP7 EATS project dealing with the introduction of GNSS to onboard ETCS, he was involved in several Shift2Rail projects and he is currently part of Europe’s Rail research projects apart from being member of the board.

jmendizabal@ceit.es