Modeling real time CBTC operation in mixed traffic networks

A simulation-based approach

MODELING REAL TIME CBTC OPERATION IN MIXED TRAFFIC NETWORKS: A SIMULATION-BASED APPROACH

Valerio De Martinis, Corresponding author
ETH Zurich
Stefano Frascini platz 5, 8093 Zurich, Switzerland
Tel: +41 44 633 2652; Fax +41 44 633 10 57; Email: valerio.demartinis@ivt.baug.ethz.ch

Ambra Toletti
ETH Zurich
Stefano frascini platz 5, 8093 Zurich, Switzerland
Tel.: +41 44 6332418; Fax: +41 44 633 1057; E-mail address: ambra.toletti@ivt.baug.ethz.ch

Ulrich A. Weidmann
ETH Zurich
Stefano Frascini platz 5, 8093 Zurich, Switzerland
Tel: +41 44 633 33 50; Fax +41 44 633 10 57; Email: weidmann@ivt.baug.ethz.ch

Andrew Nash
Emch+Berger AG Bern
Schlösslistrasse 19, 3008 Bern, Switzerland
Tel: +43-676-933-0483; Email: andrew.nash@emchberger.com

Words n. 5102
Tables n. 2
Figures n. 7
Total equivalent words: 7352

ABSTRACT

Vehicle automation and continuous connection with communication networks are the key innovations currently redefining transport systems. Just as autonomous cars are rapidly changing road transport, increasing railway automation will help to maximize the use of infrastructure, reduce schedule unreliability, increase safety, and improve energy efficiency. However, railway operations are fundamentally different from road-based transport systems and automation must be specifically tailored to railway characteristics.

This paper investigates how optimization methods (e.g., energy reduction) can be integrated into mixed traffic railway operations supported by CBTC (Communications Based Train Control) systems and ATO (Automated Train Operation) systems are present; this assumption, although currently futuristic, is a target for technology development. Thus, a method for simulation-based modeling is proposed to precisely evaluate potential trajectory modifications by taking into consideration the entire process, from the decision to modify train operation, through the computing phase to final implementation. The approach generates solutions that fully consider the surrounding rail traffic and schedule constraints. This proposed simulation based optimization method was tested by developing real time alternative trajectories for energy efficient driving and then applying them in a case study using the OpenTrack railway simulation model. The case study results showed that it was possible to integrate optimization methods with simulation models to provide instructions that can be implemented via CBTC. In the case study example, it was possible to achieve a general energy saving of 23% on average with an increased travel time of 8% on average.

Keywords: CBTC, ATO, energy efficiency, simulation, optimization

1. INTRODUCTION

Railways play an important role in today's transport system and they will become more relevant in the future because of their better performance compared with other transport modes, such as higher energy efficiency, higher capacity, and higher safety at high speeds.

A key problem holding back railway growth is the high cost of building new infrastructure and long payback periods that do not support fast implementation. One exception is the implementation of selected automation and communication technologies, which are becoming comparatively less expensive and more powerful (thereby increasing the benefits of implementation). Given the importance of automation and communications, they have become a major theme for current and future railway research.

This paper describes research on simulation modeling of possible real time train operation scenarios. Simulation modeling is an important tool for scenario evaluation because proper modeling of train operations will allow evaluating many possible real time strategies for improving railway operations (e.g., increasing capacity, reducing energy use, etc.). The main technological requirements for implementing these strategies is the use of Communication Based Train Control (CBTC) and Automatic Train Operation (ATO) systems. These systems provide the required level of interaction between trains and the control center so that automated methods for increasing the adherence to planned conditions during real time operation can be used. Figure 1 illustrates the main functions of a CBTC system operating with ATO (same notation as in (*1*)).

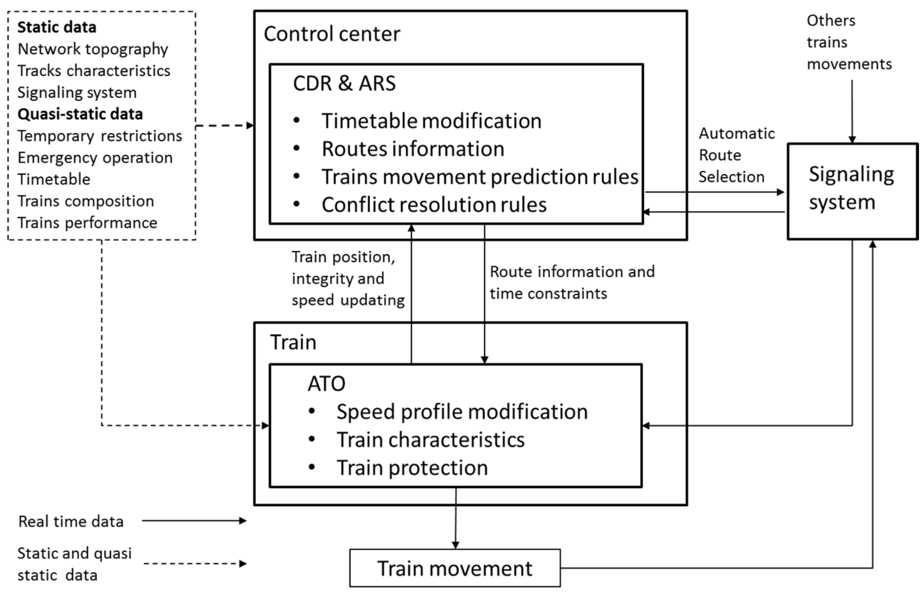

FIGURE 1. Functional scheme between traffic control center and trains.

This paper addresses several key questions surrounding real time implementation of railway optimization via CBTC systems. More specifically how railway simulation can be integrated with these optimization methods, including questions of timing, simulation methods, and simulation quality. Section 2 presents a literature review. Section 3 describes the implementation of optimized train scheduling via real time train control. Section 4 summarizes the simulation modeling process used in the research. Section 5 presents results of applying the methodology in a case study on energy saving driving optimization. Section 6 presents conclusions and recommendations for further research.

2. LITERATURE REVIEW

One of the most important trends in railway operation is the technological development of communication and signaling systems, towards a time-continuous data exchange between traffic control centers and trains. CBTC architectures have been developed following this trend (*2, 3*), with the purpose of increasing capacity, enhancing train performance and ensuring safety. The most interesting applications are in metro systems (*4, 5, 6*), and in railways where CBTC systems are combined with ATO systems (*7, 8*.

Combining a CBTC system with ATO systems for train operation control enables railways to increase adherence to (new) instructions and reduces the variability given by human driving behavior (*9, 10*). Alternatively, rescheduling models can be applied (*11, 12, 13*), specifically developed to consider manual driving behavior in the optimization process, such as the number of instructions given to the driver (*14, 15*).

Among all rescheduling applications using these technologies, those related to improving energy efficiency are growing fastest (*16, 17*), due to requirements for improving the environment, market liberalization and increasing private investments on infrastructures and services.

Some research has developed bi-level optimization procedures, i.e. at both the railway network level through rescheduling and the single train level through speed profile optimization. Operational schemes may differ substantially: for example, the optimization of speed profiles can be coupled with collaborative sub-models for optimizing train departures to increase the reuse of recovered energy during braking at arrivals (*18*). Another solution is to develop integrated solutions for both synchronizing train movements to maximize the use of regenerative energy and optimizing driving strategy to minimize tractive energy consumption (*19*). Moreover, rescheduling routines may generate alternative energy efficient trajectories to be included in the set of solutions considered for a multiobjective optimization problem (*20*).

This paper focuses on the operating aspects that may differ when considering mixed traffic networks and multiple users. This condition is still futuristic, although most of the technology involved is already available, so the aim is to develop an appropriate modelling framework that considers the operating conditions of CBTC systems coupled with ATO systems, in order to reproduce real time implementation and to evaluate current and alternative trajectories. Thus, this paper proposes and formulates an optimization framework with a specific application for generation of energy efficient trajectories. In particular, the use of simulation based optimization models allow for a better definition of travel times in both normal operation and energy saving operation, thus preserving (re) scheduling from possible unplanned delays.

3. IMPLEMENTING OPTIMIZATION SCHEMES IN REAL TIME

This section summarizes the functional requirements of real time operation in order to build an appropriate evaluation model. This is particularly important since it clearly highlights the weaknesses of the proposed optimization processes and therefore describes the needs for further research.

The research is based on normal operation of a generic train. In this case, real time optimization results for improving train operation efficiency may only be applied when they do not compromise services to customers. The starting assumption is that, although it may be theoretically possible to build a database of possible optimized solutions (i.e., energy efficient driving scenarios) in advance, the variety of cases and conditions that may occur during railway operations would lead to an extremely large database, which may be unfeasible to manage. Therefore, real time optimization is better since it returns a specific solution for any given operating condition.

On the other hand, developing a solution in real time takes time, and the developed solution must still be feasible and optimal when it is implemented. The solution development process is composed of several phases, each of which take time:

a) Detection of optimization condition: is there time to implement an optimized solution? In this phase, the time needed to allow modification of normal operation are checked. If delays are present, they should be smaller than time reserves.
b) Current operation forecasting (normal condition simulation): where will the train be when the optimized solution is available? This phase is normally developed by traffic control centers, which are able to forecast train trajectories on a continuous basis.
c) Evaluation of starting time and position for optimal solution implementation: where and when is the best place to implement the optimized solution? This phase is crucial since the starting conditions during implementation may differ significantly from those chosen as input in the optimization phase.
d) Optimization at expected starting time: how should the train operation be optimized at the time of implementing the optimization? The optimization should be conducted after fixing the timeavailabilities (e.g. time reserves) required to provide alternative solutions and must respect (re)scheduling constraints when implemented.
e) Verification of current operating condition at expected start time: have the operating conditions at optimization implementation changed from the projected conditions? The starting condition assumed in developing the optimized operating solution must match the current operating condition before implementation. Any deviation, will lead to a deviation of the optimized trajectory.
f) Implementation of the optimal solution: how long does it take to implement the solution using the automated system? This ensures that the optimization solution can be effectively implemented through ATO systems.

Figure 2 presents a schematic illustration of these six phases. Phases a) and b) are part of existing processes at the traffic control center, and the updating of the train's expected trajectory is almost continuous. Phase c) can be can be fixed or known a priori, e.g. based on previous experience. However, this phase is fundamental for the goodness of the result. The time interval needed for fulfilling these three tasks (T_eval) is relatively small. Results are the black line profile, the expected arrival time (t_a) and the estimated time for implementing the alternative solution (t_s).

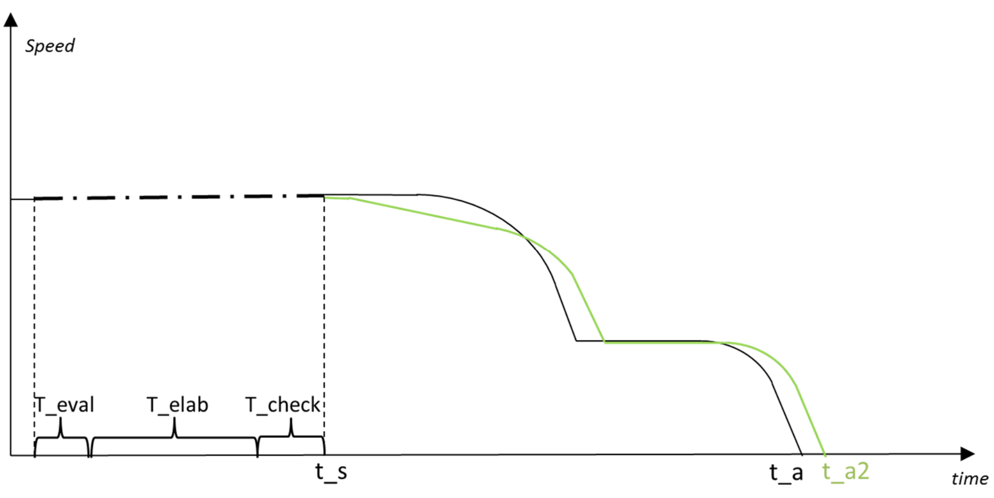

FIGURE 2. Schematic representation of time requirements for real time optimization of train operations

Phase d), the optimization of train operation, may take from few seconds to minutes for output (t_elab), depending on the complexity of the operating conditions. Mainly the optimized solution will start from t_s defined in phase c) considering also the expected position and speed of the train. It is clear that the optimization routine must produce a solution before t_s. The output is the green profile and the new time arrival (t_a2).

In phase e) the congruence between the current position and speed of the train and the expected ones at t_s are checked. If the two values match, then phase f) can begin (T_Check).

This description of the optimization process shows clearly the importance of railway simulation in the development and implementation of optimized solutions. The next section describes simulation in more detail.

4. SIMULATION AND RAILWAY OPERATIONS OPTIMIZATION FRAMEWORK

Microsimulation models today allow planners to consider a wide variety of aspects that influence train movement. Since the main intention of this research is the modeling of real time operation, it is clear that a time-step-based microsimulation, which calculates the dynamic parameters of the considered trains and then updates the signaling system status accordingly, is the appropriate choice for obtaining the required detailed information. Figure 3 illustrates the conceptual framework of the simulation environment used in this research. As shown, the input database in the microscopic environment mainly consists of infrastructure characteristics, rolling stock performance data and specifications, signaling system functionalities and the timetable.

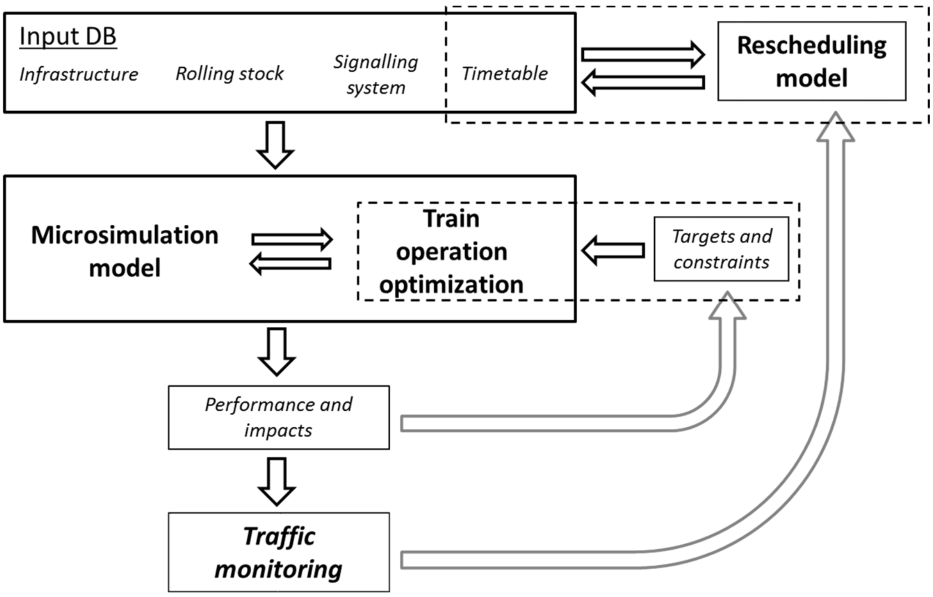

FIGURE 3. The simulation framework with fundamental relationships. Bold text represents the main models and tools composing the framework, italic text highlights data and information used during the whole process.

The microsimulation model updates train motion data (time, position, acceleration, speed) and train traction data (tractive efforts, resistances, power, energy consumed) for each time step. The interaction with the train operations optimization model is realized through a closed iterative loop where simulation results are used to estimate the control variables for train operation optimization that will then be used to drive the next iteration of simulation.

The simulation results (estimated performance and impacts) can also be used to redefine the train operation optimization's targets and constraints (e.g. constraints on running or dwell times). While the modifications in expected train motion are used to estimate delays and their possible propagation. Finally, the traffic monitoring process checks overall traffic conditions, in terms of potential delays and possible conflicts. These traffic-related variables then form the input of decision processes for possible rescheduling solutions. The mathematical formulation of the entire process can be generalized in the following set of equations.

$$(y_1, \dots, y_h) = SIM(\hat{x}_1^{opt}, \dots, \hat{x}_n^{opt}, x_{n+1}, \dots, x_{n+m}) \tag{1}$$

$$(\hat{x}_1^{opt}, \dots, \hat{x}_n^{opt}) = \arg\min \mathrm{G}\left(F(\hat{x}_1, \dots, \hat{x}_n)\right) \tag{2}$$

$$\begin{array}{l} \hat{x}_1 \le \hat{x}_1^{max} \\ \quad \cdots \\ \hat{x}_n \le \hat{x}_n^{max} \end{array} \tag{3}$$

$$\begin{cases} t_i(y_1, \dots, y_h) \le t_i^{max}(y_1, \dots, y_h) \\ s_i(y_1, \dots, y_h) = s_i^{max}(y_1, \dots, y_h) \end{cases} \forall i = 1, \dots, L \tag{4}$$

Where output ($y_1, \dots, y_h$) from the simulation process (SIM) depend on both exogenous variables ($x_{n+1}, \dots, x_{n+m}$) and control variables ($\hat{x}_1^{opt}, \dots, \hat{x}_n^{opt}$) that come out from the train operational optimization process in eq 2. The train operational optimization process will minimize the measure of performance G (e.g. delays, energy consumption, etc.) computed with the function F. The optimization process is constrained by the maximum possible performance of the trains (eq 3) and by operational constraints given from railway network traffic conditions (eq. 4).

The railway network traffic conditions, in particular can be grouped into time constraints and distance constraints. Time constraints ensure that the optimization solution respects specific schedule times such as arrivals and departures at specific points (e.g. nodes, junctions, etc.), while the distance constraints ensure that the distance to travel is achieved. Both these constraints are defined with respect to a given discretization *i = 1… L* of the travel distance to cover.

It is worth highlighting that output from the simulation model can be mainly grouped into two categories: single train outputs (e.g., speed profiles, energy consumed, running time, and dwell time at stations) and railway network traffic statistics (e.g., delays at stations, runs cancelled, conflicts, etc.). These traffic statistics mainly give indications on the performance changes and impacts when modifying, even partially, the railway operations.

5. CASE STUDY APPLICATION

Case Study Description

The simulation and railway operations optimization framework outlined above was tested in a case study to help identify the main requirements for future applications. The case study considers a railway operations optimization for reducing energy consumption on a mixed traffic network. It was performed on a widely tested simulation network of the Railway Simulation Lab located at the Institute for Transport Planning and Systems at ETH Zurich. The simulation network is a perfect replica of a physical model built in collaboration with the Swiss National Railways (SBB) and Siemens. It reproduces typical infrastructure solutions from the Swiss rail network and is used to model railway network operations.

TABLE 1. Trains and model parameters for numerical experiment.

Train number	Train type	Length [*m*]	Weight [*Tons*]	Number of scheduled stops
401, 402	Intercity (IC)	318	782	2
3041, 3042	Regional (IR)	200	382	4
17021, 17022, 17023, 17024	Suburban (S)	74	123	5
69071	Freight (FR)	898	1682	0

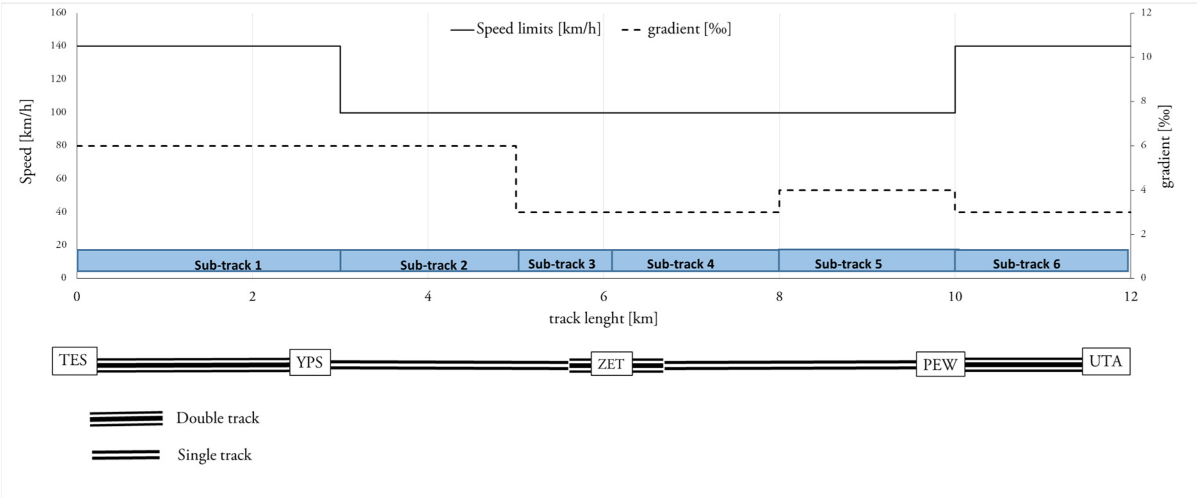

FIGURE 4. Case study railway network.

Table 1 summarizes the characteristics of trains modeled in the case study and Figure 4 summarises the main infrastructure qualities of the test network.

The case study experiment considered 9 train courses. In the experiment, a simulation and optimization framework was used to compute alternative trajectories to enable the trains to consume less energy while maintaining service punctuality. These alternative trajectories were then sent to the trains via CBTC systems. An essential requirement for applying the energy optimization was that the rail traffic conditions were normal (i.e., trains were operating generally on schedule).

Considering the specific train stops, the changes in gradients and in speed limits it is possible to identify six track sub-sections with constant values of these characteristics. Then optimal speed targets could be assigned for each track sub-section.

The case study area was assumed to be a compensation zone, i.e. an area where the traffic is relatively low. This means train operations can be modified relatively easily in order to recover from delays, avoid conflicts, etc. (modeling described in (*21*)). In the case study tests, the considered time window for operation was between 8:00 and 9:00 AM.

In this research all the simulations were carried out using the OpenTrack (*22*) railway simulation model via the OpenTrack Application Program Interface (API). An Application Program Interface (API) allows outside processes to interact with the source code of a software program. In this case the optimization model communicates with the simulation environment via the OpenTrack API to obtain simulation results. This approach is appropriate because it allows practitioners and researchers to test their solutions on a common environment and eliminates the need to consider differences when comparing different “customized” simulation environments and the consequent necessity of validating simulation results. The energy reduction optimization code was based on enetic Algorithms, which provides a fast response and stable results (see also other experiences such as (*23*)), developed in MatLab (see (*24*) for description).

Optimization process example: energy efficient trajectories

The optimization model tested in the case study was specified from (2)-(4) by considering target speeds (TSP) as control variables for energy consumption and assuming the availability of supplement times for implementing alternative trajectories. The optimization model for solving the energy saving problem is defined for a single train. It is formulated as follows:

$$[TSP^*] = arg \min_{TSP} E\ [\boldsymbol{G}(TSP)] \tag{5}$$

Subject to the following constraints:

$$TSP \quad \leq TSP_{max} \tag{6}$$

$$T_i^{TSP} \leq T_i^{max} \tag{7}$$

$$S_i^{TSP} = Dist_i \tag{8}$$

where: *TSP* is the vector of train motion parameters chosen for optimization and *TSP** is the vector of its optimal values, TSP_{max} is the vector of maximum allowed values of TSP; these values are defined as the minimum values between the maximum performance of rolling stock and maximum performance allowed by the infrastructure/service.

E(.) is the total tractive energy spent, estimated using the function ***G*** representing the simulation-based procedure in which parameters of infrastructure, rolling stock, timetable and signaling system are already defined; T_{TSP} is the time needed to run the specified interstation track with the TSP parameters; T^{max} is the maximum permitted running time for the specified interstation track, including the additional time dedicated to the implementation of the optimized SP; S^{TSP} is the distance covered with TSP parameters and *Dist* is the length of the specified interstation track.

Different energy optimization strategies can be considered depending on the chosen vector of control variables and the type of analyzed services. Here, the optimization of target speeds was chosen to be consistent with future research on the Swiss National Railways ADL system. The ADL system (from German: Adaptive Lenkung, adaptive train control) is a driver advisory system that optimizes energy consumption for a given conflict-free schedule by providing the driver with relevant speed information. Trajectories are developed based on conflict-free conditions between two planned stops, and these conditions are then ensured by the (re)scheduling processes.

Results: simulation-based optimization

Since the purpose of the case study was to reproduce the operating phases of a train subjected to real time speed modification designed to reduce energy consumption, the following hypotheses are formulated:

- Time available for optimization is defined considering arrival times at stops and reserve times. Constraints for individual trains are defined considering the surrounding traffic.
- Suburban trains (blue lines) have a tight schedule so they will not be considered for optimization.
- The stop in ZET is not used by any of the trains being considered for operational modifications, therefore track sub-sections 3 and 4 were merged.

- IR trains stop at 2 intermediate stations. However, their operational time constraints are only at the final stations, respectively TES and UTA. This means that, at intermediate stations, the operating rule is to leave the station after stopping not before a given time. Dwell time at stations has been fixed at 60 seconds.
- Considering the presence of ATO systems, trajectory variation during running due to stochastic events can be neglected. Therefore, dwell times at planned stops are the only stochastic variables to be considered.

The optimization was conducted with the aim of reducing energy consumption. In the proposed case study, the final solution was reached within a few seconds and therefore was fast enough to enable the alternative trajectories to be transmitted to the trains via CBTC and implemented by the trains.

The optimal solution (optimal speed targets for the 5 track sub-sections) was reached after 65 iterations. The entire optimization process was completed in approximately 24 seconds, therefore t_s has been considered 40 seconds after the entrance at the control area in order to consider also possible T_eval, and T_check (see section 3 for definitions).

Figure 5 illustrates the train trajectories in a normal time-distance graph. It shows trajectories for both the NOP (normal operation) and ESOP (energy saving operation) scenarios. NOP is the initial scenario from which optimized solutions are generated and it represents the forecasted trajectory in normal operation (continuous lines). The ESOP scenarios are shown in dashed lines. In the case study, suburban trains were considered as fixed due to a required punctuality of the service and a tight schedule (so there are only solid lines).

The other services, i.e. InterCity (IC), InterRegio (IR) and freight trains have some tolerances that enable them to be considered for alternative trajectories to reduce energy consumption. Each alternative trajectory is generated with the constraint that it does not impact service punctuality to the surrounding trips. Table 2 highlights the main differences between the ESOP and NOP trajectories in percentage terms of additional time spent and energy saved. It is interesting to note that the optimization trends tend to reduce the acceleration phases, since these phases use the most energy. Figure 6 finally shows energy trends for the case study trains. Energy saving trajectories allow saving up to 23% on average of energy consumed in NOP conditions.

TABLE 2. ESOP speed targets and additional time required.

Trains		**401**	**402**	**3041**	**3042**	**67091**
TSP_1	[m/s]	29.7	30.3	27.9	28.0	26.7
TSP_2	[m/s]	26.6	27.5	26.9	27.5	24.7
TSP_3	[m/s]	26.9	26.7	26.4	26.7	24.4
TSP_4	[m/s]	27.2	26.9	26.3	26.9	24.6
TSP_5	[m/s]	29.1	29.4	26.1	27.1	25.8
Additional time	[%]	*9.60*	*8.16*	*8.32*	*6.35*	*8.57*

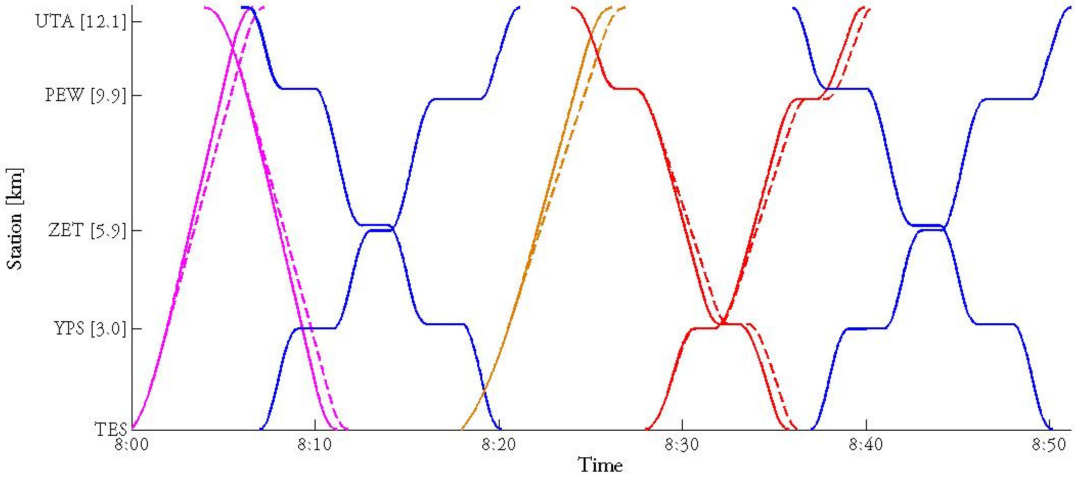

FIGURE 5. Comparison between NOP trajectories and ESOP trajectories. From left InterCity trains (pink) IC 401 and 402, Suburban trains (blue) 17021 and 17022, Freight train (yellow) 69071, Interregional trains (red) IR 3041 and 3042, Suburban trains 17023 and 17024. Continuous lines represent NOP trajectories, dashed lines represent ESOP trajectories.

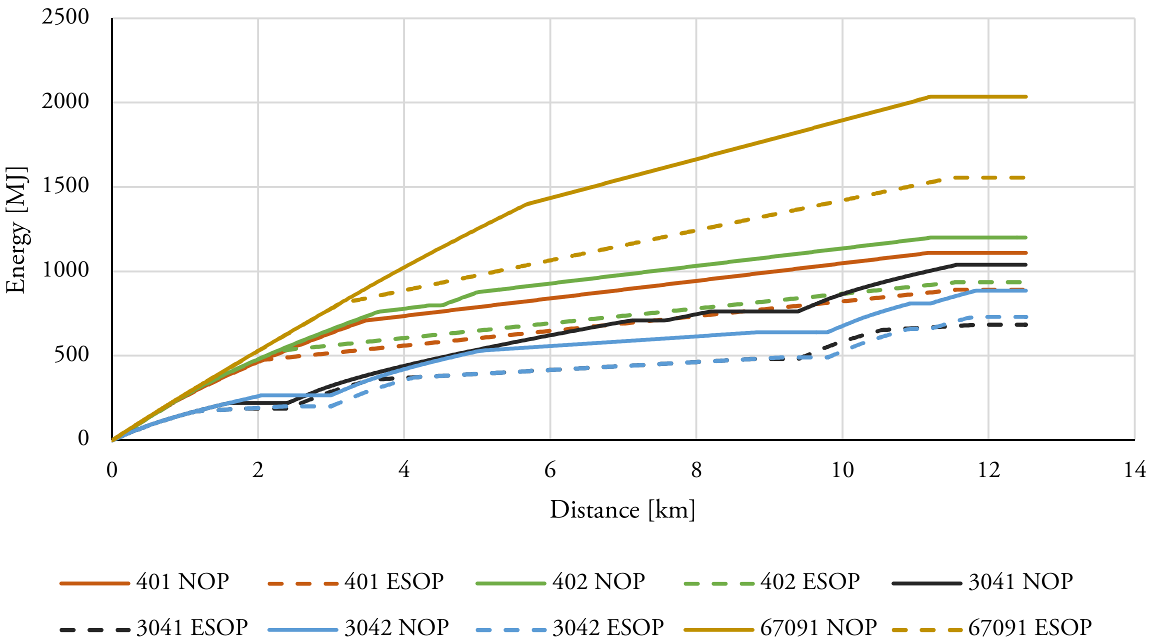

FIGURE 6. Energy consumption in NOP and ESOP conditions.

Discussion

This paper's main intention is to provide an overview on the simulation processes of future real time operation, including trajectory modification, with CBTC systems and ATO systems in mixed traffic networks. As an example of a possible application, we analyzed the processes for generating alternative trajectories oriented to reducing energy consumption.:

Regarding the approach. The approach must fully consider the time available to be used for calculating trajectory modifications and the estimated time needed to communicate new instructions to the trains. The paper's central assumption is that alternative trajectories can be developed by on board systems (ATO systems), since the wide variety of train services and possible configurations make it difficult for centralized software applications (e.g., at the traffic control center) to effectively develop trajectories (which is possible for highly uniform operations such as metro lines).

Regarding the optimization model. It is interesting to note that the optimization of target speeds developed in the case study tend to minimize the differences between them, leading towards a "green wave" strategy. This is logical when considering the high demand for energy during acceleration phases. These results may differ in case high values of gradients and/or introduction of coasting phases in the optimization strategy are present.

Regarding the possible time variation. Dwell times and initial delays are the two main uncertainties to consider during optimization. Since operation at stations are critical mainly in urban areas, here only initial delays are considered according to the specific case. Concerning passenger trains, in figure 7 it is possible to see how the initial delay can affect the delay observed at the final station. The figures that show parallel trends denote the absence of disturbances during the trip, while the figure for IR 3041 shows several modifications due to dispatching rules, when an extended delay required it to wait at the station until the successive suburban train passes. Some small disturbances can also be observed in train IC 402, due to dispatching rules when approaching YPS station. However, the figures show that within approximately 25 seconds of initial delay, the alternative trajectories are not affected from surrounding operations, and, in fact, operate like the on-time trajectories.

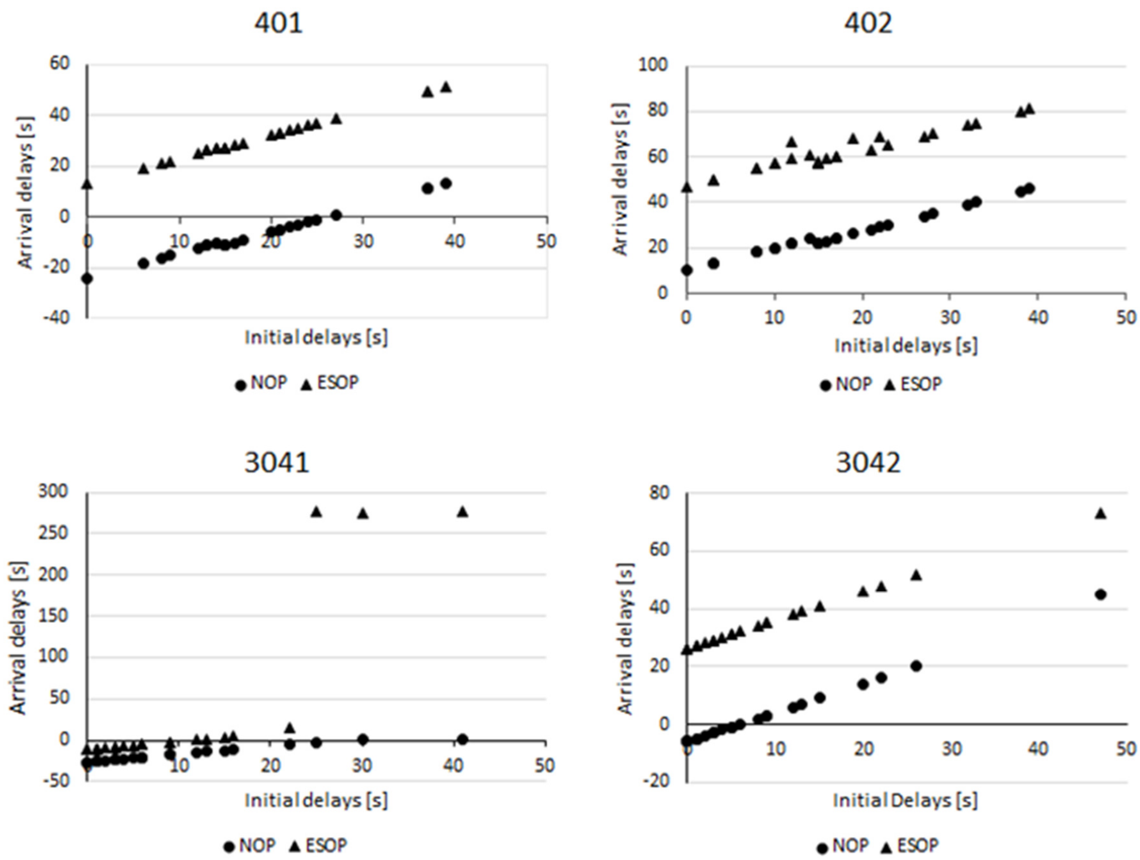

FIGURE 7. Comparison between initial delays and arrival delays, both in NOP and ESOP conditions.

6. CONCLUSIONS AND FURTHER DEVELOPMENTS

This paper proposes an approach to simulation modeling considering CBTC and ATO systems in mixed traffic conditions. Although automation is not yet being used extensively in mixed traffic networks, this will change in the coming years, similar to what is happening on roadways with autonomous cars. The results of this research shows that even with typical constraints during real operations, such as computing times for sophisticated optimizations, there is good potential for optimizing train operation in real time and for implementing improved solutions. In particular, focusing on the energy efficiency example tested in the research, a potential energy consumption reduction of 23% on average is possible, with limited time extensions (8% on average). This potential energy saving can be effectively realized if the considered ATO systems are used to implement the optimized trajectories.

The proposed approach has been shown to work, further research will be targeted on the evaluation of different models for generating alternative trajectories, for multi objective purposes (e.g. conflict avoidance and energy consumption reduction). Moreover, it is worth to deepen real time rescheduling processes when applied without time and space constraints, i.e. rescheduling should be computed and implemented wherever and whenever it is required.

REFERENCES

1. Mitchell, I. The Sustainable Railway: Use of Advisory Systems for Energy Savings. *IRSE News*, 2009, Vol. 151, pp. 2-7
2. Zhu, L., F.R. Yu, B. Ning and T. Tang. Design and performance enhancements in communication-based train control systems with coordinated multipoint transmission and reception. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 15, 2014, pp. 1258-1272.
3. Wang, H., T. Tang, C. Roberts, C. Gao, L. Chen, and F. Schmid. A novel framework for supporting the design of moving block train control system schemes. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, Vol. 228, 2014, pp. 784-793.
4. Carvajal-Carreño, W., A.P. Cucala and A. Fernández-Cardador. Fuzzy train tracking algorithm for the energy efficient operation of CBTC equipped metro lines. *Engineering Applications of Artificial Intelligence*, Vol.53, 2016, pp. 19-31.
5. Xun, J., K. P. Li, and Y. Cao. An optimization approach for real-time headway control of railway traffic. *IEICE Transactions on Information and Systems*, Vol. E98D, 2015, pp. 140-147.
6. Wu, Z., and Y. Wang. Urban Rail Simulation Platform Control System Design Based on Fault Detection. In: *ICTE 2015 - Proceedings of the 5th International Conference on Transportation Engineering*, 2015, pp. 3200-3206.
7. Domínguez, M., A. Fernández, A. P. Cucala, and P. Lukaszewicz. Optimal design of metro automatic train operation speed profiles for reducing energy consumption. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, Vol. 225, 2011, pp. 463-473.
8. Allotta, B., L. Chisci, P. D'Adamio, S. Papini, and L. Pugi. Design of an Automatic Train Operation (ATO) system based on CBTC for the management of driverless suburban railways. In: *Proceedings of the 12th IMEKO TC10 Workshop on Technical Diagnostics: New Perspective in Measurements, Tools and Techniques for Industrial Applications*, 2013, pp. 84-89.
9. Gong, C., S. Zhang, F. Zhang, J. Jiang, and X. Wang. An integrated energy-efficient operation methodology for metro systems based on a real case of Shanghai Metro Line One. *Energies*, 7, 2014, pp. 7305-7329.

10. Ning, B., J. Xun, S. Gao, and L. Zhang. An integrated control model for headway regulation and energy saving in urban rail transit. *IEEE Transactions on Intelligent Transportation Systems*, 16, 2015, pp. 1469-1478.
11. Cacchiani, V., D. Huisman, M. Kidd, L. Kroon, P. Toth, L. Veelenturf, and J. Wagenaar. An overview of recovery models and algorithms for real-time railway rescheduling. *Transportation Research Part B: Methodological*, 63, 2014, pp. 15-37.
12. D'Ariano, A., F. Corman, D. Pacciarelli and M. Pranzo. Reordering and local rerouting strategies to manage train traffic in real time. *Transportation Science*, 42, 2008, pp. 405-419.
13. Corman, F., A. D'Ariano, A. D. Marra, D. Pacciarelli, and M. Samà. Integrating train scheduling and delay management in real-time railway traffic control. *Transportation Research Part E: Logistics and Transportation Review*, April 2016, Article in Press and Available Online.
14. Sicre, C., A.P. Cucala, and A. Fernández-Cardador. Real time regulation of efficient driving of high speed trains based on a genetic algorithm and a fuzzy model of manual driving. *Engineering Applications of Artificial Intelligence*, 29, 2014, pp. 79-92.
15. Albrecht, T., C. Gassel, A. Binder, J. Van Luipen. Dealing with operational constraints in energy efficient driving. In: *IET Conference on Railway Traction Systems (RTS 2010), Proceedings,* 2010*,* pp. 1-7.
16. González-Gil, A., R. Palacin, P. Batty, and J.P. Powell. A systems approach to reduce urban rail energy consumption. *Energy Conversion and Management*, 80, 2014, pp. 509-524.
17. Yang, X., X. Li, B. Ning, T. Tang. A survey on energy-efficient train operation for urban rail transit. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 17, 2016, pp. 2-13
18. Su, S., T. Tang, and C. Roberts. A Cooperative Train Control Model for Energy Saving. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 16, 2015, pp. 622-631.
19. Li, X., and H. K. Lo. An energy-efficient scheduling and speed control approach for metro rail operations. Transportation Research Part B: Methodological, Vol. 64, 2014, pp. 73-89.
20. Toletti, A., V. De Martinis, and U. A. Weidmann. What about train length and energy efficiency of freight trains in rescheduling models? *Transportation Research Procedia*, Vol. 10, 2015, pp. 584-594.
21. Caimi, G. C. *Algorithmic Decision Support for Train Scheduling in a Large and Highly Utilised Railway Network*. Shaker Verlag GmbH, Germany, 2009
22. Nash, A., and D. Huerlimann. Railroad simulation using OpenTrack.In *Advances in Transport,* No. 15, 2004. pp. 45-54.
23. Zhao, N., C. Roberts, S. Hillmansen and G. Nicholson. A Multiple Train Trajectory Optimization to Minimize Energy Consumption and Delay. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 16, 2015, pp. 2363-2372.
24. De Martinis V and U. A. Weidmann. Definition of energy-efficient speed profiles within rail traffic by means of supply design models. *Research in Transportation Economics*, Vol. 54, 2015, pp. 41-50.