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Multi-train trajectory optimization for energy efficiency and delay recovery on single-track railway lines

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ABSTRACT

This paper proposes a novel multi-train trajectory optimization for single-track lines. We restrict our attention to delay cases aiming at finding optimal speed profiles, which reduce delays and save energy consumption. A multi-train trajectory optimization method is proposed to find optimal meeting locations, arrival/departure times, and speed trajectories of multiple trains within the time and speed windows. The proposed method first finds timetable constraint sets for trains under delayed situations. The timetable constraint sets provide drivable, feasible, and energy-efficient time and speed windows along the trains' routes. The multi-train trajectory optimization method uses minimizing energy consumption and reducing delays as the objective functions, and takes into account each train's operational constraints as well as constraints to avoid conflicts between adjacent trains. Three driving strategies of delay-recovery, energy-efficient and on-time driving, are proposed and combined in the optimization objective selection for different delay scenarios. The multi-train trajectory optimization is formulated as a multiple-phase optimal control problem and solved by a pseudospectral method. The proposed method is applied in case studies of opposite trains running on a Dutch single-track railway corridor with different initial delay scenarios. The results show that our method is able to produce a feasible schedule with energy-efficient speed trajectories for all interacting trains.

1. Introduction

Delays affect the performance of railway networks and the quality of service provided to passengers and shippers. When delays occur, drivers are responsible for getting the delayed trains back to the original or rescheduled timetable. The process of getting delayed trains back to schedule is called delay recovery. It is more energy-efficient to recover the delay gradually over several legs of the journey than to recover quickly (Albrecht et al., 2015). However, the delayed train will often interact with other trains, causing a further delay propagation through the system and thereby impacting the energy-efficiency of many trains. In particular, on single-track lines, trains have limited possibility of meeting and overtaking. Trains cannot enter the single-track lines that are occupied by opposite trains, and trains in the same directions must follow each other's path sequentially, until an overtaking or passing track is reached at stations or sometimes at loops. Those limitations increase the possibility of delay propagation. Therefore, even the experienced drivers find it hard to achieve an efficient train operation once the train is delayed or affected by delayed trains on the single-track lines.

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To improve the performances of train drivers, train driver advisory systems (DAS) are proposed, which provide train drivers with information and driving advice and helps them to drive the train in an efficient manner. A DAS needs an optimal train trajectory (speed-distance curve and time-distance curve along the train's journey), based on which driving advice is computed accordingly. The train trajectory optimization (TTO) problem is to find the optimal trajectory by optimal control theory. Generally, the optimization aims at minimising the energy consumption and maintaining the timetable, with consideration of the constraints of train characteristics, track gradients, curves and speed limits. In the last few decades, TTO has drawn a lot of attention in the literature. Wang et al. (2011), Albrecht et al. (2016a), and Scheepmaker et al. (2017) provide comprehensive surveys from different views. Wang et al. (2011) reviewed the numerical approaches for solving the train trajectory optimization problem. Albrecht et al. (2016a) focused on the state-of-the-art of using Pontryagin's Maximum Principle (PMP) to find the key principles of optimal train control. Scheepmaker et al. (2017) provided surveys on the energy-efficient train control and energy-efficient train timetable problems. The solution methods of the TTO problem can be divided into two categories: indirect methods and direct methods (Wang et al., 2011). PMP is a typical indirect method, which has been successfully used in train trajectory optimization (Albrecht et al., 2016a). With the application of PMP, the TTO problem is converted to a problem of finding the optimal sequence of optimal control regimes (maximum power, cruising, coasting, and maximum braking) and the switching points between the regimes for a range of different circumstances and train types. Finding the optimal sequence and switching points is a difficult problem except for simple cases such as a single speed limit and flat track (Albrecht et al., 2016b). Direct methods were developed more recently and expanded quickly because of their advantages over indirect methods (Scheepmaker et al., 2017). Direct methods transcribe a optimal control problem to a nonlinear programming problem (NLP), which is then solved by existing NLP solvers. For instance, pseudospectral methods have been successful applied by Wang et al. (2013), Wang and Goverde (2016a) and Ye and Liu (2016) in solving the TTO problem.

Under delay circumstances, the interactions from neighboring trains cannot be ignored, which have drawn attention recently. Some researches reflect the interactions as dynamic speed limits on train movements imposed by signaling systems. Albrecht (2009) considered the driving strategies to move a train through conflict areas. The target was to slow down the train before critical conflicts (red signals) and then pass critical infrastructure elements with shortest possible delay, in this way, reducing energy costs and avoiding unscheduled stops. Three driving strategies – reactive driving, optimal anticipating driving, and safe anticipating driving – were proposed to achieve this target. Yun et al. (2011) provided solutions to identify the optimal approaching speed for the optimal anticipating driving strategy. The optimal speed enables the train to leave the conflict area as soon as possible. A heuristic method was then developed to attain the optimal speed trajectory. Wang and Goverde (2016a) focused on the single-train trajectory optimization problem with consideration of dynamic speed limits imposed by the signalling system. Two different driving strategies, a signal response policy and green wave policy, were developed to respond to signals and to avoid yellow signals. The signal response policy refers to actively adjusting the train speed according to the signal aspects. A green wave policy means anticipating to slow down the train in front of a conflicting area to make the train face only green signal aspects. A different green wave policy was first proposed in Corman et al. (2009), in which the green wave policy allows trains to wait only at their scheduled stops. Wang and Goverde (2016a) extended the green wave policy by allowing regulating speeds and running times for more efficient driving. The case studies in Wang and Goverde (2016a) show that a green wave policy saves more energy consumption than the signal response policy.

Other researchers optimize multi-train trajectories together with consideration of the interactions between neighboring trains. Albrecht et al. (2011) provided a numerical algorithm to find interaction times that allows each affected train to finish on time wherever possible and minimises total energy consumption for the whole set of trains. The interaction times can be transmitted to DASs on each of the trains (trajectory optimization modules), which will set strategies to meet these times. Further work is required to extend to situations where interaction locations and sequences may change. Yang et al. (2012) provided a mathematical model for multiple trains on a railway network. The model aims at minimizing total energy consumption and running times of all trains, while satisfying the constraints to ensure the feasibility of multi-train operations, which include headway constraints, vehicle speed limit constraints, passenger riding comfort constraints, and dwell time constraints. The control strategies of every involved train are the decision variables of the multi-train model. A genetic algorithm (GA) integrated with simulation was designed to find the optimal control strategies. Zhao et al. (2015) studied the trajectory optimization problem of multi-trains, considering the trade-off between reduction in train energy usage against increases in delay. The research focused on following trains with a fixed block signaling system in a delayed situation. A multi-train simulator and three searching methods, namely, enhanced brute force, ant colony optimization, and a genetic algorithm, were adopted to find the optimal trajectories. A case study of four following trains showed that the algorithm is able to reduce energy consumption and interactions between trains. However, the three searching methods cost long computation times to find optimal solutions, which needs future improvement for real-time application. Yin et al. (2016); 2017) addressed the train schedule and reschedule problem with dynamic passenger demands, with consideration of multiple trains' energy-efficient speed profiles. Wang and Goverde (2016c) studied the delay recovery problem of the two successive trains in the same direction. A two-train trajectory optimization method was developed to compute two trains' trajectories simultaneously, which takes into account not only each train's operational constraints, but also the constraints on keeping safe distances between the two trains. The green wave policy was adopted to ensure that the trains run safely under all green signals to avoid frequent stop/start behavior and thus improving train operation efficiency.