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Balancing energy consumption and risk of delay in high speed trains: A three-objective real-time eco-driving algorithm with fuzzy parameters

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ABSTRACT

Eco-driving is an energy efficient traffic operation measure that may lead to important energy savings in high speed railway lines. When a delay arises in real time, it is necessary to recalculate an optimal driving that must be energy efficient and computationally efficient.

In addition, it is important that the algorithm includes the existing uncertainty associated with the manual execution of the driving parameters and with the possible future traffic disturbances that could lead to new delays.

This paper proposes a new algorithm to be executed in real time, which models the uncertainty in manual driving by means of fuzzy numbers. It is a multi-objective optimization algorithm that includes the classical objectives in literature, running time and energy consumption, and as well a newly defined objective, the risk of delay in arrival. The risk of delay in arrival measure is based on the evolution of the time margin of the train up to destination.

The proposed approach is a dynamic algorithm designed to improve the computational time. The optimal Pareto front is continuously tracked during the train travel, and a new set of driving commands is selected and presented to the driver when a delay is detected.

The algorithm evaluates the 3 objectives of each solution using a detailed simulator of high speed trains to ensure that solutions are realistic, accurate and applicable by the driver. The use of this algorithm provides energy savings and, in addition, it permits railway operators to balance energy consumption and risk of delays in arrival. This way, the energy performance of the system is improved without degrading the quality of the service.

1. Introduction

Railways are considered energy efficient compared with other transport modes such as air travelling (Givoni, 2007). However, the concern for socioeconomic sustainability and climate change has led to the establishment of certain energy reduction goals gathered in the Paris Agreement of 2015 that affects railway sector (IEA and UIC, 2016). These energy reduction goals also affect high speed railways (HSR), which are expanding throughout the world. With this regard, many developments and research are being carried out in order to reduce the energy consumption of HSR (Hasegawa et al., 2016).

Eco-driving is considered a key measure to reduce the energy consumption of railway systems. It consists in designing the train driving in a journey to fulfill a target running time, minimizing the energy consumption. Eco-driving can be applied in the short-

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midterm and does not require high investments.

The first study on eco-driving was developed by Ichikawa in Ichikawa (1968). He applied the Pontryagin's Maximum Principle to a very simplified train dynamics model and obtained, for the first time, the optimal regimes of the train control (Ichikawa, 1968). These regimes are maximum acceleration, cruising, coasting and maximum braking.

Since then, numerous works have followed this research line improving the train model and applying a variety of optimization techniques. These techniques can be classified in analytical methods and numerical methods (X. Yang et al., 2016).

Most of analytical methods are based on the optimal control theory. Thus, they make use of the Pontryagin's Maximum Principle to obtain the energy efficient regimes and, using these results, apply different algorithms to obtain the optimal switching points between the efficient regimes. Among these algorithms it can be found: constructive algorithms (A. R. Albrecht et al., 2013; Howlett et al., 2009; Khmelnitsky, 2000; Liu and Golovitcher, 2003; Su et al., 2013; J. Yang et al., 2016), Dynamic Programming (T. Albrecht et al., 2013; Lu et al., 2013; Miyatake and Ko, 2010; Miyatake and Matsuda, 2009), Sequential Quadratic Programming (Gu et al., 2014; Miyatake and Ko, 2010) and Lagrange multiplier method over the discretized problem (Rodrigo et al., 2013). Other analytical methods are based on transforming the optimal control problem into a non-linear problem and solving it directly (Wang et al., 2014, 2013). Analytical methods can produce the optimal solution of the problem and, in most cases, using low computational times. However, the complexity of the problem and the requirements for obtaining the analytical solution lead to simplifications in the train model. Inaccuracies in the solutions could demand several recalculations of the train speed profile when applying it in a real-life case (Howlett et al., 1994).

On the contrary, numerical methods do not require simplifications in the train model, and any constraint related to passengers' comfort or the driving commands can be included. Therefore, the solutions can be obtained from models as detailed as necessary and fulfilling any operational restriction to be applied in real life. Numerical methods have also widely been applied to the eco-driving problem. Different numerical methods can be found in literature: direct search algorithms (De Cuadra et al., 1996; Wong and Ho, 2004a), Brute Force (Zhao et al., 2017), Monte Carlo Simulation (Tian et al., 2017), Artificial Neural Networks (Acikbas and Soylemez, 2008; Chuang et al., 2009) and nature inspired optimization algorithms such as Genetic Algorithm (GA) (Bocharnikov et al., 2010; Chang and Sim, 1997; Lechelle and Mouneimne, 2010; Li and Lo, 2014; Lu et al., 2013; C. Sicre et al., 2012; Wong and Ho, 2004b, 2003; Yang et al., 2012), multi-population genetic algorithm (GA) (Huang et al., 2015; Wei et al., 2009), GA combined with fuzzy logic (Bocharnikov et al., 2007; Cucala et al., 2012; Hwang, 1998; Sicre et al., 2014), Differential Evolution (Kim et al., 2013), Ant Colony Optimization (Ke et al., 2012; Lu et al., 2013; Yan et al., 2016), Simulated Annealing (Keskin and Karamancioglu, 2017; Xie et al., 2013), Indicator Based Evolutionary Algorithm (IBEA) (Chevrier et al., 2013), Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Carvajal-Carreño et al., 2014; Domínguez et al., 2014) and Multi-Objective Particle Swarm Optimization (MOPSO) (Domínguez et al., 2014; Fernandez-Rodriguez et al., 2015).

The majority of these eco-driving studies are oriented to an offline application during the planning stage. However, the interest in the online application of eco-driving algorithms during the regulation stage is rising. Regulation deals with the real-time objective of bringing the rail traffic to the scheduled operation. In most of HSR, as in the Spanish case, each train is responsible for its own regulation. For instance, if a delay is detected in a particular train, the regulation strategy will be oriented to change the initial speed profile to a faster one to consume the time margin included in the timetable and make up the timetable deviation. In this scenario, online eco-driving algorithms may play a fundamental role to ensure not only the quality of the service but also the energy efficiency of HSR.

The main challenges of online eco-driving are the weather conditions, delays of other trains and the limitations in the movement authority produced by signals. These situations could derive in a delay on the train demanding a quick response to achieve the punctuality requirements. From the point of view of the optimization process, short calculation time and accuracy in results are important features to evaluate the performance of an online eco-driving algorithm (Wang and Goverde, 2017a).

Most of papers proposing online applications of eco-driving algorithms make use of analytical methods because of their calculation time performance compared to other techniques (Coleman et al., 2010; Gu et al., 2014; Howlett et al., 1994; Khmelnitsky, 2000; Liu and Golovitcher, 2003; J. Yang et al., 2016).

Some of these pieces of research do not make an online application but other authors studied their proposals to be applied to recover perturbed situations. In Ghaviha et al. (2017), the authors propose a DAS for railway systems, where the optimization of the different driving possibilities is performed off-line and a set of binary files are generated (the execution time is 20 min for each file) that are later read in real time on-board the train.

In Albrecht et al. (2010), the Maximum Principle is applied and the optimal switching points are obtained taking into account the influence of the signals on the train movement. A numerical algorithm was applied in Albrecht et al. (2011) to study energy-efficient delay recover strategies. Wang and Goverde proposed a multi-phase model for optimizing the train trajectory of single and multiple trains with the objective of recovering delays, saving energy and avoiding conflicts (Wang and Goverde, 2017b, 2016a, 2016b). This model considers the effect of the signalling system and it is solved using the pseudospectral method.

On the other hand, some authors proposed the use of nature inspired optimization algorithms that can be combined with detailed train models to obtain, on one hand, more accurate solutions, and, on the other hand, more applicable solutions making it more comfortable for passengers and train drivers (Chang and Sim, 1997; Wong and Ho, 2004b). A GA was applied in combination with a multi-train mathematical model in Yang et al. (2012) to find the optimal control of trains while headway, comfort, and dwell time constraints are observed. In Sicre et al. (2014), a GA is used in combination with a detailed simulation model to obtain new driving commands when a delay is detected. The trade-off between energy consumption and delays was studied in Zhao et al. (2015). The optimal trajectories of trains were obtained by means of an enhanced brute force method, ACO and GA.

Apart from the particular optimization technique used, another important issue when solving eco-driving problems is to