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A driver advisory system with dynamic losses for passenger electric multiple units

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ABSTRACT

Driver advisory systems, instructing the driver how to control the train in an energy efficient manner, is one the main tools for minimizing energy consumption in the railway sector. There are many driver advisory systems already available in the market, together with significant literature on the mathematical formulation of the problem. However, much less is published on the development of such mathematical formulations, their implementation in real systems, and on the empirical data from their deployment. Moreover, nearly all the designed driver advisory systems are designed as an additional hardware to be added in drivers' cabin. This paper discusses the design of a mathematical formulation and optimization approach for such a system, together with its implementation into an Android-based prototype, the results from on-board practical experiments, and experiences from the implementation. The system is based on a more realistic train model where energy calculations take into account dynamic losses in different components of the propulsion system, contrary to previous approaches. The experimental evaluation shows a significant increase in accuracy, as compared to a previous approach. Tests on a double-track section of the Mälaren line in Sweden demonstrates a significant potential for energy saving.

1. Introduction

According to a report by the International Energy Agency and International Union of Railways, from 1990 to 2011, the use of electricity was doubled in the railway sector. Moreover, the share of electric traction motors in trains has increased to 86% for freight and 81% for passenger trains in Europe, with the highest increase during the last decade (IEA and UIC, 2015). Further, rising energy prices and environmental concerns call for solutions to reduce the energy consumption of electric trains. Short term target set by the European Union is to decrease the energy consumption of the railway sector with 30% by 2030. According to Scheepmaker et al. (2017), a reduction in energy consumption in the railway sector can be done in four different fields: more energy efficient rolling stock, optimizing the use of rolling stock based on capacity demand, minimizing auxiliary systems energy requirements, energy efficient time tabling and energy efficient train control (EETC). The focus of this paper is on energy efficient train control using a driver advisory system (DAS), which gives instructions to the driver in order to minimize the energy consumption while keeping the time plan. In this paper we present the design and implementation

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of a driver advisory system for regional electric multiple units as an Android application. The optimization technique used is discrete dynamic programming. The process includes both mathematical aspects (i.e. designing an enhanced train model and optimization technique), together with the aspects around designing a DAS on Android, including user interface, memory management and calculation time. Moreover, the train model used in this paper has a higher accuracy with regard to energy calculations, compared to similar published research articles.

1.1. Related work

The mathematical basis behind designing a driver advisory system is speed profile optimization, in which an optimum speed profile for a certain train configuration on a certain track profile is sought. The research results of one of the first major works in this field was published in 1968 presented by Ichikawa (1968), and during decades different mathematical algorithms have been suggested for solving this problem. Traditionally, an energy efficient speed profile of a train has been found by considering phases consisting of maximum acceleration, coasting (driving with no tractive effort) and then maximum brake. The goal in coast control is to find the optimum speed for coasting. Chang and Sim (1997), Lechelle and Mouneimne (2010), Erchao et al. (2014), Bocharnikov et al. (2010) and Wong and Ho (2004b) solved the coast control problem using genetic algorithms for a single train, and Yang et al. (2012) used a similar approach to solve the coast control problem on a network of trains. Acikbas and Soylemez (2008) introduced an approach based on the combination of a genetic algorithm and an artificial neural network for multi-train operation. Artificial neural networks have also been used by Hui-Jen et al. (2008) for the single train problem. Shashaj et al. (2016) considered the problem of joint optimization of multiple train speed profiles in order to increase the overall energy recovered from the braking system. An approach for the problem based on heuristic search methods was introduced by Wong and Ho (2004a). Further, the problem is also solved for catenary-free operation of trains using particle swarm optimization (Colak et al., 2012). There have also been studies to use dual heuristic programming to solve the coast control problem (see Sheu and Lin, 2011; Jih-Wen and Wei-Song, 2012).

Other than coast control, the problem of speed profile optimization can be seen as an optimal control problem. Over time, different approaches based on this view have been proposed. The maximum principle is used to solve the problem for the single train operation (Geng et al., 2015; Howlett, 2000; Khmelnitsky, 2000; Liu and Golovitcher, 2003; Nguyen Thanh, 2010; Shuai et al., 2013; Wang and Zhu, 2014). Miyatake and Ko (2007a,b) solved the problem for both single and multiple train operation under a DC feeding circuit. Other than the mentioned approaches, a variety of other algorithms such as ant colony optimization and fuzzy control are also studied to solve the problem of energy efficient train optimal control (Yasunobu et al., 1983). Yin et al. (2014) presented a heuristic solution based on drivers' experiences and reinforcement learning, concluding that their approach surpass the driving style of the experienced drivers in terms of energy optimization and punctuality. Further, sequential quadratic programming was used by Miyatake and Matsuda (2008) to solve the problem for hybrid electric trains. Dynamic programming (DP) is also one of the promising approaches to solve the energy efficient train optimal control, as it provides a global solution to the optimization problem. Moreover, DP facilitates handling constraints on state variables (Miyatake and Ko, 2010). Miyatake and Haga (2010), Ko et al. (2004) and Miyatake et al. (2009) solved the problem for catenary-free operation of electric trains with onboard energy storage device using DP. The solution includes quick charging of the energy storage device. Franke et al. (2000) used kinetic energy per mass unit as one of the state variables when solving the problem for normal electric trains using DP, arguing that using kinetic energy per mass unit instead of velocity, eliminates some of the nonlinearities of the problem and facilitates the piecewise analytical solution for the rest of the nonlinearities. Haahr et al. (2017) presented a novel fast approach based on dynamic programming to solve the problem. Yin et al. (2016) proposed a stochastic programming model for metro rescheduling to jointly optimize the energy consumption together with the passengers' travel time and delay and used an approximate dynamic programming approach to solve the problem. DP is even used for joint optimization of multiple trains speed profiles. Zhou et al. (2017) presented a novel space-time-velocity grid for multiple train operation and tackle the problem using a heuristic approximate dynamic programming approach. Dynamic programming have also been used to solve similar problems in other transport sections such as minimizing the fuel consumption of heavy trucks (Hellström et al., 2010, 2009). A list of different energy efficient train control methods is presented by Scheepmaker et al. (2017).

Although the scientific literature on speed profile optimization and optimal control of electric trains is quite mature, not much work has been published regarding the practical implementation of such algorithms for designing a driver advisory system. Nevertheless, many such proprietary driver advisory systems are available in the market for different types of trains with different types of operation. Panou et al. (2013) presents a full review on current available DAS systems in the market.

According to Miyatake and Ko (2010), in optimizing train operation 8 different characteristics should be considered: braking system, tractive effort curve, running resistance, track profile, energy storage systems, power loss in the motors and inverters, losses in the grid and the signaling system. The last two are considered as the characteristics of the power and train network. The research presented in this paper is focused on the catenary operation of a single electric multiple unit without any energy storage system. Further, losses in the grid and interaction between different trains in the network are also excluded from the scope of this research.

Scheepmaker et al. (2017) notes that EETC is struggling between more accurate models and minimizing the calculation time. Hence, the focus here is to present a more accurate model for energy calculation in an EETC approach, while keeping the calculation time to the minimum. As such, it is of great importance that the energy losses of the train system is modeled at a sufficient detail. In the scientific literature, the train models used for EETC problem only consider a constant fixed