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Multi objective particle swarm optimization algorithm for the design of efficient ATO speed profiles in metro lines

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ABSTRACT

One of the strategies for the reduction of energy consumption in railways systems is to execute efficient drivings (eco-driving). This eco-driving is the speed profile that requires the minimum energy consumption without degrading commercial running times or passenger comfort. When the trains are equipped with Automatic Train Operation systems (ATO) additional difficulties are involved. Their particular features make it necessary to develop accurate models that optimize the combination of the ATO commands of each speed profile to be used by the traffic regulation system. These commands are transmitted to the train via encoded balises on the track with little channel capacity (bandwidth). Thus, only a few and discrete values of the commands can be sent and the solution space of every interstation is made up of a relatively small set of speed profiles. However, the new state-of-the-art of signalling technologies permit a better bandwidth resulting in an exponential solution space. This calls for new methods for the optimal design of the ATO speed profiles without an exhaustive simulation of all the combinations. A MOPSO algorithm (Multi Objective Particle Swarm Optimization) to obtain the consumption/time Pareto front based on the simulation of a train with a real ATO system is proposed. The algorithm is able even to take into account only the comfortable speed profiles of the solution space. The fitness of the Pareto front is verified by comparing it with a NSGA-II algorithm (non-dominated sorting genetic algorithm II) and with the real Pareto front. Further, it has been used to obtain the optimal speed profiles in a real line of the Madrid Underground.

1. Introduction

Metropolitan systems are expanding day by day and becoming some of the major energy consumers in the cities. It has become a global concern to reduce the energy consumption and costs in railway systems (Feng et al., 2013b). Different technologies, developments or strategies are being researched and tested from the point of view of traffic management (Jia and Zhang, 1994; Fay, 2000; Abril et al., 2008; Feng et al., 2013a; Feng et al., 2013b), optimal use of regenerative braking in order to improve the energy efficiency (Domínguez et al., 2012; Falvo et al., 2011) and driving optimization.

The objective in efficient driving (eco-driving) design is to find the speed profile that requires the minimum energy consumption without degrading commercial running times. With this aim, various mathematical models have been applied. However, the difficulties involved in the analytical resolution of the problem lead to a number of simplifications in the approaches (Albrecht et al., 2011; Franke et al., 2000, 2000; Khmelnitsky, 2000; Ko et al., 2004; Miyatake and Ko, 2010; Su et al., 2013) which makes their application to real cases impractical. The approaches based on simulation offer more promising alternatives. They do not require simplifications in the models and enable an accurate calculation of the running times and the energy consumption. A number of optimization techniques have been used in combination with simulation – Genetic Algorithm (Bocharnikov et al., 2010, 2007; Cucala et al., 2012b; Lu et al., 2013; Sicre et al., 2012; Wong and Ho, 2003, 2004b; Yang et al., 2012), Artificial Neural Networks (ANN) (Chuang et al., 2009, 2008), a combination of both the techniques (Acikbas and Soylemez, 2008) and direct searching methods (De Cuadra et al., 1996; Wong and Ho, 2004a). ANN have also been used to optimize the traffic regulation by learning traffic data (Lin and Sheu, 2011).

However, additional difficulties are involved when the trains are equipped with Automatic Train Operation systems (ATO) as seen in many metropolitan trains today. The function of this equipment on board the train is to drive the train automatically according to a preprogrammed speed profile (Bocharnikov et al.,

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2007; Chang and Xu, 2000). The ATO equipment provides a control reference to the train's traction equipment for observing the maximum and safe speed limits and for stopping the train at stations. The intervention of human drivers is limited just to the opening and closing of the doors and to the starting up of the train after each stop. As a result, the running times and energy consumptions are quite stable when the signalling systems do not affect the circulation of trains.

A set of preprogrammed ATO speed profiles are available per interstation with different running times and energy consumption. Depending on the running time required, the centralized traffic regulation system on-line selects the ATO speed profile to be executed by each train between two stations (Fernandez et al., 2006). Each speed profile is programmed as a combination of the ATO commands that are transmitted to the train from the track via encoded balises or antennas.

The traffic regulation systems performance and the total energy consumption strongly depend on the off-line design of these ATO speed profiles. Studies on the driving efficiency in metropolitan trains with ATO can be found in Bocharnikov et al. (2007), Chang and Xu (2000), Khmelnitsky (2000), Wong and Ho (2004a) and Zhou et al. (2011). However, they do not satisfy realistic constraints and control capabilities of any particular ATO system or the ATO model is simplified (De Cuadra et al., 1996), which makes difficult their implementation in real ATO equipments. The particular features of the ATO systems, the short inter-stations in metropolitan lines and the differences of a few seconds between the ATO speed profiles to be designed, make it necessary to develop accurate models that optimize the combination of the ATO commands of each speed profile to be preprogrammed in the equipment.

Most of the metropolitan railways use four alternative speed profiles per interstation (Fernandez et al., 2006). The first one (number 0) is characterized by the minimum running time (flat-out), that is to say, applying maximum available acceleration, speed and deceleration. The remaining profiles are slower and correspond to lower energy consumption. The maximum time gap between the fastest and the slowest is bounded as an operational criterion (Cucala et al., 2012a; Domínguez et al., 2011).

Typically, the configuration variables of the ATO systems consist of four commands: coasting speed, re-motoring speed, speed holding value and braking deceleration rate. These commands are transmitted to the antenna located under the train via encoded balises on the track which permit a limited amount of data bits to be transmitted due to the channel capacity (Gill and Goodman, 1992). Thus, only a few and discrete values of the commands can be sent providing each interstation with a relatively small solution space of speed profiles consisting of the combinations of these discrete values. This way, the optimal solution can be found by exhaustive search, simulating all the possible combinations as described in Domínguez et al. (2011).

Other studies have also looked for saving energy under the framework of the current fixed-block signalling system (Ke et al., 2009). However, the new state-of-the-art of signalling technologies such as CBTC permit a better communication capacity (bandwidth) with high-resolution train location determination, and bidirectional train-to-wayside data communications (IEEE, 1999). More command values can be sent since the increment is smaller, thus resulting in an exponential solution space.

Therefore, this calls for a new method for the optimal design of the ATO speed profiles without an exhaustive simulation of all the combinations. Some studies are already trying to find optimal driving in CBTC systems (Gu et al., 2011), however, a realistic ATO is not taken into account in these cases either. Some studies have proposed algorithms based on GA (Bocharnikov et al., 2007; Lu et al., 2013; Wong and Ho, 2004a), or ACO (Ant Colony Optimization) (Lu et al., 2013) for the single objective optimization, but they do not consider either realistic characteristics of the ATO equipment. In this paper, the authors propose a multi-objective evolutionary algorithm that has better performance that GA, to obtain the consumption/speed Pareto front based on the detailed simulation of a train equipped with a real ATO system.

Evolutionary computation is inspired by biological processes found in nature. Genetic algorithm (GA) modeled on the Darwinian evolutionary paradigm is the oldest and the best known Evolutionary Algorithm (EA). It imitates the natural processes of selection, cross-over and mutation to search for optimum solutions in massive search spaces.

Another very recent algorithm belonging to the class of biologically inspired methods is the Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995, 2001, 1997). It has already been used in railways problems (Jamili et al., 2012). PSO imitates the social behavior of insects, birds or fish swarming together to hunt for food. PSO is a population-based approach that maintains a set of candidate solutions, called particles, which move within the search space. During the exploration of the search space, each particle maintains a memory of two pieces of information: the best solution (*pbest*) that it has encountered so far and the best solution (*gbest*) encountered by the swarm as a whole. This information is used to direct the search. EAs are primarily used in the optimization of a single objective although they have been further extended and used in the simultaneous optimization of *multiple* objectives. They seem to be especially suited to multi-objective optimization problems (MOOP) due to their abilities to search simultaneously for multiple Pareto optimal solutions and to perform better global search of the search space (Mitchell, 1996).

Many EAs have been developed for solving MOOP. Examples are: NSGA-II (Deb et al., 2002) which is a variant of NSGA (non-dominated sorting genetic algorithm); SPEA2 (Zitzler et al., 2002) which is an improved version of SPEA (Strength Pareto Evolutionary Algorithm) and PAES (Pareto Archived Evolution Strategy) (Knowles and Corne, 2000). These EAs are population-based algorithms that possess an in-built mechanism to explore the different parts of the Pareto front simultaneously.

The PSO is also extended to solve MOOP. Among those algorithms that extend PSO to solve multi-objective optimization problems are Multi-objective Particle Swarm Optimization (MOPSO) (Coello et al., 2004), Non-dominated Sorting Particle Swarm Optimization (NSPSO) (Li, 2003) and the aggregating function for PSO (Parsopoulos and Vrahatis, 2002). The performance of different multi-objective algorithms has been tested in Coello et al. (2004). MOPSO is found to be the best in covering the full Pareto front of all the functions used. In addition, it is found to converge with a low computational time. Therefore, the MOPSO algorithm has been selected in this paper for finding the Pareto front with the optimal ATO speed profiles of a real metropolitan line. The algorithm is based on simulation to calculate in detail the realistic characteristics of the ATO driving and the type of commands that can be sent to the train. In this paper a MOPSO algorithm is proposed for the first time for solving this design problem more efficiently that the previous algorithms proposed for the single objective function.

In Section 2, the simulation model of a train equipped with an ATO system is introduced. Then, the MOPSO algorithm for the design of ATO speed profiles is detailed in Section 3. Section 4 describes first some tests carried out in order to tune the MOPSO parameters and to validate it. Then, a case study of a real line is described and the results of some interstations are shown, and the proposed MOPSO algorithm is compared to the multi-objective algorithm NSGA-II (non-dominated sorting genetic algorithm II) to show the better performance of the first. In addition, the comfort and operational constraints are introduced in the design of the