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Driver's control optimization under uncertainties to reduce energy consumption of high-speed trains.

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Abstract

Controlling the energy consumed by our systems has turned to be an important stake in today's world and especially in the railway domain, since transports constitute one of the largest energy consumers. In the railway sector, the energy consumed by high-speed trains depends on many variables such as the vehicle characteristics, the rolling environment of the train, or its speed profile. To limit the impact of the latter, drivers are asked to follow a target trajectory defined by crossing points along the journey. Nevertheless, we can remark that important differences in energy consumption still exist. The industrial objective of this work is to define a model, able to describe the train dynamics and to propose an optimization method, which aims to minimize the energy consumption under uncertainties.

This work is composed of two parts. First of all, two probabilistic models are defined to describe the train longitudinal dynamics (based on a Lagrangian approach) and its energy consumption. This model is fitted using a Bayesian calibration from measurements carried out on commercial trains. Particular attention is paid to the description of the rolling environment of the train and of the vehicle characteristics. Afterwards, the robust optimization of the command under uncertainty is performed using the CMA-ES method to minimize the energy consumed while punctuality, security, and comfort constraints are respected.

On the scientific point of view, this work has enabled the development of original methods to introduce non-linear physical and punctuality constraints in a probabilistic framework by means of order relations. The driver's command is chosen as the optimization variable instead of the train speed, as it is often the case in literature. It facilitates the transposition of the developments to real systems. In addition, many energy measurements are used to calibrate and validate the models. The rolling environment and the vehicle characteristics are carefully defined from existing case study. To conclude, algorithms are developed for the robust optimization of the problem including uncertainties on both objective function and constraints.

Keywords: High-speed train dynamics, Bayesian inference, Optimization under constraints and uncertainty.

1 Introduction

Reducing the energy consumption has turned to be an important stake in today's world and particularly in the railway sector, since transports constitute one of the largest energy consumers. For this reason, the railway companies pay close attention to the energy consumption from the design to the recycling phase, especially the maintenance and the exploitation processes. Recently, controlling the energy has become even more crucial because of the growing demand stemming from the increase of the trains' frequency, as well as their speed. To achieve this objective, three levers can be activated: modify the rolling environment, the vehicle characteristics, or the speed profile. The present work focuses on the speed profile optimization of trains because important variations of energy consumption have been noticed for different drivers with the same vehicle and equivalent rolling conditions.

Trains evolve in a complex network and their speed profile should not be determined erratically. Effectively, reducing or increasing the speed of a train may have an impact on other journeys. To limit this impact, drivers are asked to follow a target trajectory defined by crossing points along the journey. Nevertheless, we can remark that differences in energy consumption still exist. For this reason, optimizing the driver's command appears to be an important challenge for the railway companies.

This project is also motivated by the active development of autonomous trains, for which the driver is going to be replaced by robust algorithms. The optimal solution may be used as a nominal target trajectory for autonomous trains, to minimize the energy consumed along the journey. It can be brought into play by modifying the target trajectory in case of specific rolling conditions.

2 Methods

The present work focuses on the optimization of trains' speed. This latter must fulfil several constraints. One reason is that it has to assure the passengers' security by respecting the speed limitation on the track; these constraints are called the *security constraints*. The second reason is that the train must arrive in the train station at a specific time and a given position with an appropriate speed; these are called the *punctuality constraints*. Finally, the passengers should not be subjected to violent accelerations or jolts; these conditions are regrouped in the *comfort constraints*. Consequently, the project can be summarized mathematically as an optimization problem under *deterministic non-linear constraints*.

However, the speed profile of the train is driven by its longitudinal behaviour on the track. The optimization supposes thus to construct accurate physical models to describe on the one hand, the train longitudinal dynamics and on the other hand its energy consumption. But the train behaviour is difficult to predict in a perfect way, because of the great sensitivity to its environment. Despite a relatively fine modelling of the track, the wind, and the vehicle, the slightest uncontrolled disturbance can modify the whole dynamic behaviour of the train. Moreover, a lack of knowledge limits the precision of the models because some quantities of the mechanical system are not well known or may vary. For example, masses depend on the ridership, aerodynamic loads and wheel-rail contact conditions depend on the weather, stiffnesses and dampers may be damaged, etc. A probabilistic model is thus introduced to include the uncertainties inherent to the system. This framework modifies the cost function and the constraints, which become random variables, and appropriate order relations need to be established to handle the uncertainties.

In this work we have also decided to optimize the driver’s command rather than the speed trajectory. This should facilitate the implementation of the algorithms on autonomous trains. Finally, the problem consists in optimizing the driver's command to minimize the mean value of the energy consumed, integrating the longitudinal dynamic behaviour of the train, and respecting the set of probabilistic constraints.

The optimal speed trajectories are ultimately compared to the experimental traffic flow and so the estimated energy savings will be discussed.

3 Results

Our approach is to build models of the train's longitudinal dynamics (from a Lagrangian formalism) and its energy consumption [1]. The train behaviour is carefully modelled and adapted to the case study. Particular attention is paid to the definition of the traction, the pneumatic, and the dynamic braking capacities that can restore a part of the energy consumed. Moreover, the track characteristics are introduced thanks to measured declivity and curvature. The amplitude and direction of the wind are defined due to the predictions of the Meteo France, providing a good description of the rolling environment.

A sensitivity analysis is then carried out to identify the parameters that have a large impact on the models. The magnitude of the model error and the distributions of the important parameters are estimated thanks to a *Bayesian formalism* [2]. The *a priori* distributions are built using the available physical knowledge (mean, variance, support). The likelihood function is defined from a set of power and speed measurements performed on commercial trains (see [3] for details). Finally, the application of a Markov Chain Monte Carlo (MCMC) method [4], the Metropolis-within-Gibbs algorithm [5], allows us to access to the *a posteriori* distributions.

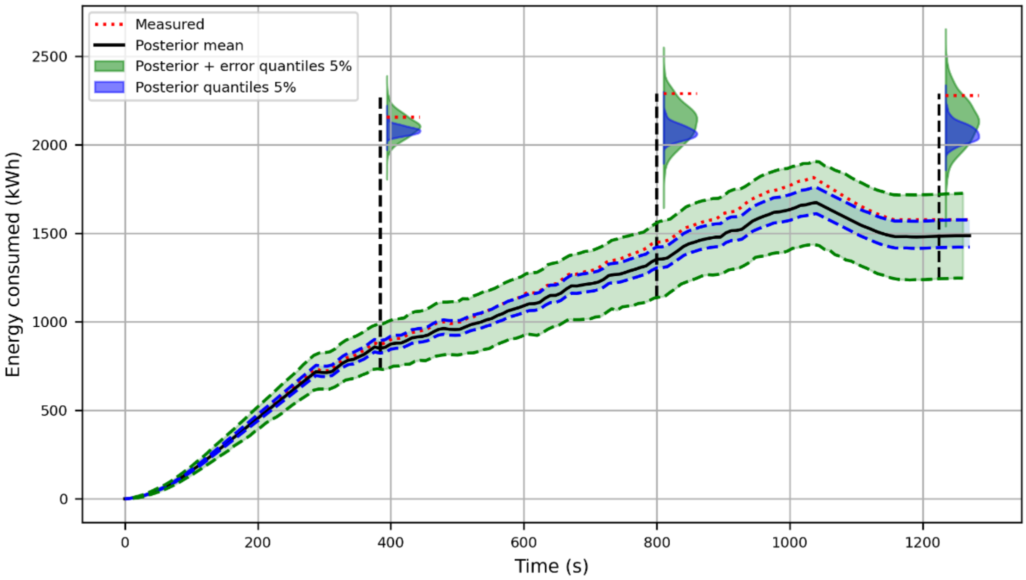

Figure 1: Energy computed by the models in function of time.

The mean (resp. 5% quantile interval) of the energy consumed from realizations of the posterior distributions is represented as the black solid line (resp. blue envelop). The green envelop stands for the 5% quantile interval for which the error is added. The energy measurements are plotted in a red dotted line. The local energy distributions of the posterior and error model are plotted at three different times.

Ultimately, a *robust optimization* method under uncertainty is achieved to estimate the deterministic driver's command, which minimizes the mean value of the energy consumed. To do so, the Covariance Matrix Adaptation - Evolution Strategy (CMA-ES) algorithm [6] is used by introducing the uncertainties as a form of noise applied to the cost function.

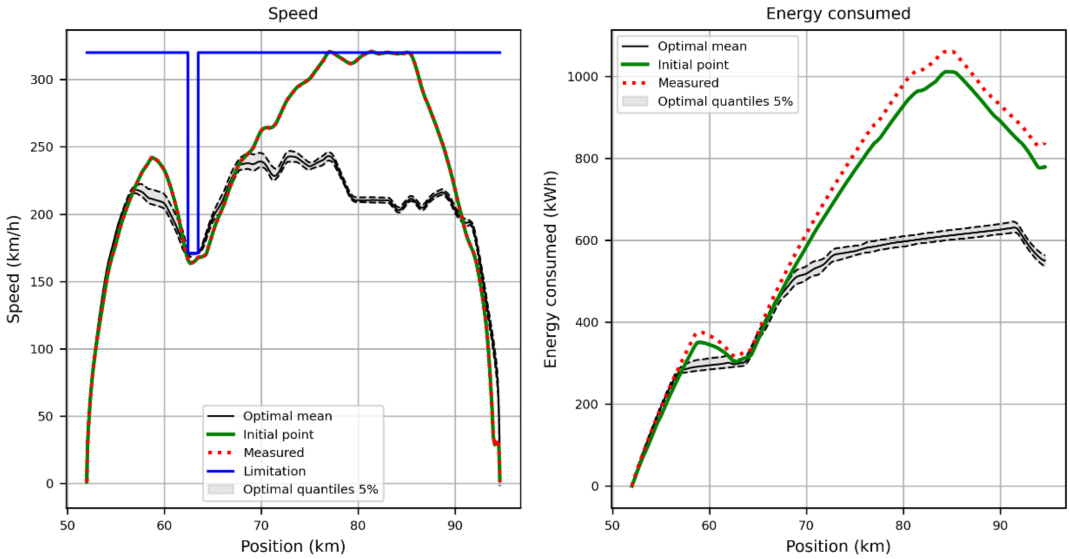

Figure 2: Speed (left) and energy consumed (right) by the optimal solution in function of position.

The optimal mean (resp. 5% quantile interval) is represented as a solid black line (resp. grey envelop). The starting point of the algorithm is plotted as a green line and the measurement as a red dotted line. The blue line stands for the speed limitation.

4 Conclusions and Contributions

This work presents several originalities. First of all, a special effort is made to ensure that the longitudinal dynamic model is representative. The errors are carefully modelled, and the parameters are calibrated thanks to energy measurements carried out on real high-speed trains. This guaranties a good representation of the real system. This set of measurements also allows the comparison of the optimal solution with real journeys. The uncertainties are examined through a Bayesian calibration. It allows to represent the variability of the measurements, the model errors, and the lack of knowledge on several physical parameters. Thus, the models constructed are general representations of the real system and they are adapted to the multiplicity of possible configurations.

On the scientific point of view, this work has enabled the development of original methods to introduce non-linear constraints in a probabilistic framework by means of order relations. The driver's command is chosen as the optimization variable instead of the train speed, as it is often the case in literature. It facilitates the transposition of the developments to real systems. In addition, algorithms are developed for the robust optimization of the problem including uncertainties on cost function and constraints.

According to the obtained results, it seems that the method is efficient. Indeed, the probabilistic model has been validated, as it is able to consider the uncertainties from different rolling conditions. The optimization method allows us to reduce the energy consumed of 25%. In case of non-perturbed journeys, this speed profile can be implemented on trains, as the algorithm directly returns the optimal traction and braking commands. Soon, by giving the optimal speed profile to drivers as an extension to the existing crossing points, they can achieve an energy saving trajectory.

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