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MODEL PREDICTIVE CONTROL OF HEAVY HAUL TRAINS

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Orientador: Alessandro Jacoud Peixoto

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"I think the big mistake in schools is trying to teach (...) by using fear as the basic motivation. Fear of getting failing grades, fear of not staying with your class, etc. Interest can produce learning on a scale compared to fear as a nuclear explosion to a firecracker."

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OTIMIZAÇÃO DA OPERAÇÃO DE TRENS DE CARGA POR CONTROLE PREDITIVO BASEADO EM MODELO

Carolina Calvo Pose Santos Neves

Março/2018

Orientador: Alessandro Jacoud Peixoto

Programa: Engenharia Elétrica

Nas operações ferroviárias, atualmente há um padrão de condução personalizado para cada combinação de trem e rota. Esse plano guia os maquinistas em termos de uma direção que seja pontual e energeticamente eficiente. No entanto, os esforços elevados nos acopladores desses trens ainda provocam acidentes e problemas de descarrilhamentos, atrasando a cadeia logística e elevando os custos operacionais. Esta dissertação de mestrado descreve uma proposta de modelagem, simulação e controle de trens de carga baseada em dados reais para lidar com esse desafio.

De fato, este trabalho propõe um modelo preditivo baseado em modelo para a condução automática dos trens, levando em consideração uma minimização multi-objetivo ponderada a fim de reduzir as forças nos engates e garantir uma operação mais segura, sem que isso se traduza em relevante gasto de combustível ou aumento de tempo de viagem considerável. A técnica de janela móvel é adotada para a predição do comportamento dinâmico do sistema, incluindo as forças de conexão dos vagões decorrentes do efeito conjunto do relevo da rota e dos esforços de tração e de freio aplicados ao trem.

Um simulador do comportamento dinâmico de trens de carga é sugerido a partir do modelo não linear apresentado e as simulações numéricas ilustram a efetividade do esquema considerado para reduzir as forças nos acopladores. A metodologia é aplicada a um trem real simulado nos trilhos da Ferrovia do Aço que corta os estados de Minas Gerais, Rio de Janeiro e São Paulo.

Abstract of Dissertation presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Master in Science (M.Sc.)

MODEL PREDICTIVE CONTROL OF HEAVY HAUL TRAINS

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Advisor: Alessandro Jacoud Peixoto

Program: Electrical Engineering

In railroad operations, locomotive engineers nowadays use a personalized driving pattern for each track/train combination. This plan serves as a guide reference for punctuality and energetically efficient travels. However, many safety issues related to the high forces experimented by the trains couplers persist, provoking accidents and derailments, which delay the logistic chain and raise operational costs. This Masters Dissertation describes a modeling, simulation and control methodology for real freight trains operation dealing with the described challenge.

In fact, this work intends to propose a Model Predictive Control automatic driving procedure taking into account a weighted multi-objective minimization that can reduce forces in the couplings without increasing significantly the trip time or fuel consumption. A moving horizon technique is adopted to predict the train handling effects of the terrain forces interacting with train tractive and braking forces.

A heavy haul train dynamic simulator is developed based on the described nonlinear model and numerical simulations illustrate the effectiveness of the considered scheme to reduce coupler forces. The methodology is applied to the "Ferrovia do Aço" railroad that passes through the States of Rio de Janeiro, São Paulo and Minas Gerais in Brazil with real train configuration.

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Chapter 1

Introduction

The railway transport is a means of transporting passengers and goods in vehicles running on a given rail network, formed by different tracks. In contrast to the road transportation, the movements of these trains are constrained to the steel rails. As a land transport system, the railroad industry has been considered an economical efficient solution due to its huge capacity as multiple wagons are coupled together.

Indeed, the weight carried by unit of energy consumed is especially high for long distances. Importantly, not only railroads are undoubtedly useful and efficient with respect to time, fuel and, consequently, costs, but they also provide that benefit with a lower carbon footprint than other modes of transportation [2].

Not surprisingly, around the world, the railroad transportation is a widely chosen manner to transport products from inland locations to ports for export and inside the countries too, minimizing logistic costs. The United States, China, Russia, India, Canada, Australia and South Africa, among others, largely use their railways for freight transportation [3]. The type of cargo can vary a lot, including ore, nickel, manganese, steel, wood, copper and coal, for example.

Particularly in Brazil, the railways are a fundamental way of conveying the agricultural and mineral production mainly concentrated in the interior of the country to the urban centers and seaports. The commodities transit presents a few challenges with exceptionally long and impressively heavy trains. In fact, freight trains in Brazil can be 3 kilometers long, with more than three hundred cars coupled together carrying thirty thousands tons, the corresponding weight of a hundred loaded trucks approximately [1].

The referred Heavy Haul Trains are a composition of wagons with only braking capabilities hauled by the locomotives, tractive vehicles responsible for moving the train forward, but also being able to brake. A diesel-electric locomotive ability to break is called dynamic braking as the electric traction motor is used as a generator to slow down the locomotives and the train in consequence. Some locomotives also have brake regeneration capabilities. On the other hand, when referring to wagons ability to break, the term air brake is then applied due to its pneumatic nature [32].

In synchronous air brakes, each car is intended to apply the same friction brake force to its wheels at the same time. However, in traditional air brake systems, the corresponding signal applied from the first locomotive of the train takes some time to propagate throughout the train and different wagons receive the compressed air brake application with delays.

In contrast, the Electronically Controlled Pneumatic (ECP) air brakes mitigate the delay and are able to provide completely independent and asynchronous commands with different magnitudes for each wagon, which is the most flexible scheme. There also exist some partially synchronous systems, in which some groups of cars share the same brake signal and grouping strategies are adopted [52].

The wagon connections play an important role on the dynamic behavior of the train. A common autocoupler encountered in trains is called a draft gear. Its nonlinearities present modeling and simulation challenges that will not be detailed in this work.

Once a few aspects of the rail industry were mentioned, as well as a brief description on trains configuration is given, it is easier to understand the challenges encountered in this segment. One of the first claims were to drive trains managing the trade off between the time it took to take the train to its destination and the fuel consumed. As a matter of fact, optimizing fuel consumption intrinsically also represent a reduction in the CO_2 emissions in the railroad operations. Thus, many scheduling techniques were proposed to solve this problem in an optimal manner, producing a driving plan [34], [21],[29], [57], [6] and [23].

Traditionally, trains have been driven manually by human drivers, the locomotive engineers, that followed a predefined sequence of power levels commands for the locomotives. They also activated air brakes in the wagons in required moments. In other words, the locomotive engineers had a plan of the track with marked points to switch tractive effort commands and brakes.

With the experience of running the same train in specific tracks, they have acquired some knowledge about critical segments and driving empirical rules started to arise. Later, the technological investment in the sector sustained software development in the direction of driving trains in an autonomous manner. In that way, empirical rules on how to better drive the train started to be replaced by mathematical and physical foundations.

Automated train operation rely heavily on accurate models that represent with fidelity the train dynamics. For this purpose, Longitudinal Train Dynamics (LTD) are defined as the train motion in the direction of the track, including the whole train and any relative movement between wagons and locomotives. The assumption of no car lateral or vertical movement is relatively common depending on the purpose of the study [59], [32].

Longitudinal Train Dynamic Simulations [14] have always had an important role in the railroad industry as they can reproduce the dynamic behavior of more than a hundred coupled heavy cars in a train, weighting more than twenty thousand tons when loaded in operations. These simulations provide insight in driving strategies and allow novel studies that shape the future tendencies in freight transportation, accelerating innovative designs.

For example, for costs reasons, the rail logistics has been considering for several decades to increase the rail throughput, that is, the amount of goods transported in a given period of time. That can be done by increasing the number of running trains or the load carried per train. As a result, the increase in the trains number of cars and the weight is a constant tendency. Economically promising, this idea has been pushing technological developments in the industry [33],[53],[40].

In that sense, Longitudinal Train Dynamics is a powerful tool in predicting how much length and weight can be added to the train still operating safely in a specific track.

Also, with heavier trains, tractive effort needs increased as well and more than one locomotive can be required in the front of conventional trains. The locomotives put together to form a single unit operation receive the same power reference simultaneously. A set of vehicles under multiple unit control is referred to as a consist. The very first locomotive is called the lead unit.

In the modern rail industry, there are a couple more possible configurations to be explored to optimize railroad operations. Indeed, weight distribution and locomotives positioning inside the train are also a known research topic. A common strategy adopted in that sense is further detailed in the Section 1.3.

Besides, with longer and heavier trains, the complexity of its driving strategies also increase, leaving room for research in faster models as well as advanced control and optimization strategies. Specially, as with the growing computational power, new possibilities can be thought that were not considered with limited simulation capabilities. Better computing schemes such as parallel computing can help LTD simulations [59].

Essentially, software inputs are the track and train characteristics, producing an optimized control schedule for the compromise represented by the fuel consumption and train speed. It generally also takes some safety criteria into account.

Certainly, that automation process requires a powerful communication network as difficulties in the radio connection can be imposed for instance by the tunnels in the trajectory. Indeed, studies on how to have an effective train communication [12] are essential to transmit acquired train position via GPS and, based on it, apply the corresponding controls. The transition to automated trains is an active research topic but nowadays the human presence in locomotives cannot be neglected. In the case of an unpredicted event, the transition to manual control is done even though it presents a higher discrepancy performance as different locomotive engineers can imply driving variations.

In order to exemplify automation operation gains in Brazil, a recent pilot test in the north of country, has shown that up to 3.5% fuel can be saved in the Estrada de Ferro Carajás (EFC), considering 892 km from Carajás Mountain in the state of Pará to the Ponta da Madeira port in the state of Maranhão, without increasing the trip time.

Estimated gains are about to R$35 million in diesel per year, with 9.4 million liters of saved fuel, representing 22.7 thousands tons reduction in CO_2 emissions annually. These savings in greenhouse gases correspond to the emissions of approximately thirty one thousand popular cars running ten thousand kilometers per year [4].

1.1 Track Characteristics

Track longitudinal slope is called grade and it is usually measured in percentages, indicating the vertical distance, positive or negative, for each 100 meters of horizontal distance. An ascending or descending grade is considered light below 1% [18], which represent one meter of vertical distance increment or decrement for each 100 meters in the horizontal. Higher grades are already said to be heavy.

In practice, there are some typically encountered territories, as listed below:

— A crest is a long ascending grade followed by a long descending grade, as shown in Figure 1.1;

— A sag is the opposite shape, with a descending grade and, in sequence, an ascending grade, as shown in Figure 1.2;

— A hogback is a rapid increase in grade followed by a decreasing grade;

— An undulating profile alternates ascending and descending grades.

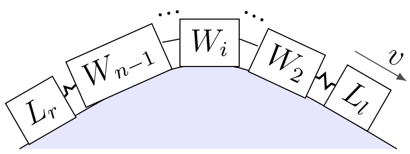

Figure 1.1 – Track Characteristics: an example of a crest.

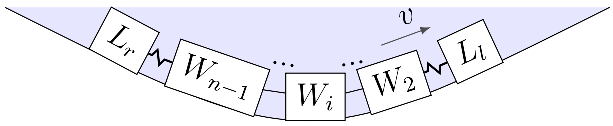

Figure 1.2 – Track Characteristics: an example of a sag.

In Figures 1.1 and 1.2, the car L_l represent a locomotive in the front, leading the train; L_r, a locomotive in the rear and W_i the wagons in the i-th position within the train.

1.2 Train Modeling and Control

As already stated, the train autopilots are based on reliable train models. Two approaches are widely used for train modeling: the point mass model and the cascade mass model.

In the former, a lumped model is adopted: all the train mass is considered to be concentrated in the train center of mass, whereas in the cascade mass model each car is viewed as a point mass connected by couplers. The point mass model is generally applied to solve the time-fuel saving scheduling problem [30], [35] not necessarily including any logic to treat forces among cars. The cascade model takes into account these in-train forces in the couplers.

The terminal time optimal control is an approach to solve the former problem [36]. Free terminal time optimal control methods can also be found in [38]. Different optimal control strategies are described in [11], [20],[31],[37], [47],[48]. Train parameter identification for optimal design is also done in [62] for high speed trains. Adaptive control and optimal power/brake distribution is applied to high speed trains considering uncertain nonlinear couplers in [50].

In general, a time-fuel optimal plan is composed of a set of power control levels, called the locomotives notches, scheduled for an entire trip, associated with a speed reference to be followed by the train. Thus, for each position of the train within the track, there is a corresponding notch and speed the train should follow to perform an optimal travel. That power and speed reference together determines the ideal tractive effort in every location.

Thus, the trip planner can find the speed and throttle for a targeted travel arrival time minimizing fuel consumption. Real constraints such as speed limits, locomotive power and tractive efforts absolute and relative rate limits are taken into account. Closed loop speed control prevent the effects of disturbances and model uncertainties. A model estimator can compensate for GPS failures and satellite communication update train data [34], [21].

1.3 Train Handling

As train has only a few locomotives capable of providing tractive efforts commands, wagons move forward pushed or pulled by the forces in the couplers connections. Wagons movement are also influenced by the terrain gravity forces: when a portion of the train is descending a gradient, gravity forces pull these cars forward whereas the wagons in ascending gradients are pulled backwards.

The train dynamics induced by the action of locomotives tractive effort and dynamic brake, coupled with wagons brakes interact with the gravity and drag forces and produce stretched or compressed couplers forces. Referring to a stretched coupler, this force is called a draft one. On the other hand, in the situation of compressed stress, this is a buff force.

As heavy haul trains are considerably long, inside the same train, one can find couplers in draft and buff situations at the same time. Indeed, in a rough terrain, it is very likely that the train will not be entirely stretched or compressed because it can be partially climbing and descending a hill simultaneously.

Also, steady in train forces are correlated with steady applications of power and braking from the locomotives and air braking, combined with the terrain grade, rolling and air resistance. It is though relevant to distinguish it from impact forces, associated with the changes in locomotive power and braking notches, along with variations in the terrain gradient.

The free slack in wagon connections produce a relative motion between vehicles known as slack action. The slack action associated with a compression is often called a run-in, whereas a stretched slack is referred to as a run-out [32].

Considering the train weight, these in-train forces can have high magnitude and thus deserve particular attention to maintain operation safety. **The ability to manage the experienced coupling forces is called train handling**. A proper controlled trip can avoid breaking the couplers, scheduling interruptions and delays, derailments and accidents. When a train breaks, it can cause a large logistic cost to the rail industry.

1.3.1 Coupler Forces Control

Nowadays, there are a number of techniques used to deal with different train handling issues. For instance, having only locomotives in the front of the train can impose difficulties to control in-train forces in the wagons far from the lead of the train [25], [40].

One well known alternative to manage this is to distribute the train total tractive force among consists in different positions within the train [41]. In this sense, the group of cars formed by the locomotives placed in the front of the train is called the lead consist. A common practice when distributing power in different consists is that of placing locomotives at the tail of the train, forming a remote consist, remotely controlled [19],[15]. If the communication is lost, the remote locomotives are forced to stop, mitigating failures.

In this case, although locomotives in the same consist are commanded through the same signal, different consists can be thought to be controlled separately. When the remote consist command follow the lead one, the operation is said to be synchronously commanded, while in the asynchronous mode they can have independent power controls. In a typical trip, lead and remote consist can pass from synchronous to asynchronous operation and vice-versa many times.

For instance, Figures 1.1 and 1.2 illustrate a train with distributed power climbing and descending a hill, where different train handling situations occur. In both pictures, a train with n cars is represented, with one lead and one remote locomotives, to exemplify distributed power.

In Figure 1.1, the terrain tends to stretch couplers passing the highest point of the hill. Experienced drivers would, in this case, brake the lead locomotive and motor the remote trying to reduce the draft forces imposed on the segment. On the contrary, a sag is responsible for compressive in-train forces and, thus, a train in the situation represented in Figure 1.2 should have its lead locomotive with motoring notches while keeping dynamic brake applied in the remote one.

In a complete track, a lot of different terrain variations occur. In an undulating track profile, as already explained, a long train can be at the same time in a sag and a crest for instance and the best decision to handle power becomes less intuitive. Imagining a train with the locomotives position of the described example, the best notches to be chosen in a train placed over a hogback could prioritize the highest absolute force, draft or buff, encountered. One could also prefer to treat draft forces over the buff ones as the former may cause more severe consequences, such as derailments, than the former.

However, there is another possibility used to handle such a situation, which is to distribute power even more, placing locomotives not only in the front and rear but also somewhere in the middle of the train, to create a middle consist. Considering the possibility of having locomotives in the lead, mid and remote consists, a train configuration is often referred as being a n_L-n_M-n_R, with n_L being the number of lead locomotives, n_M, the number of mid locomotives and n_R the number of remotes. For instance, a conventional unique lead locomotive free tail train would be called a 1-0-0 and a 3-2-2 train would have three lead locomotives, two mid ones and two remotes.

In the presence of a mid consist, it could in theory run independently from the other two, but instead that mid locomotive usually follow either the lead consist commands or the remote ones to simplify the power distribution scheme. During a trip, a virtual fence can be imagined moving between consists, so that the mid locomotives can impose the same lead or remote planned power. Thus, there exist algorithms to automate the optimal manner of moving this virtual fence with respect to train handling [40], [64].

The train control problem possess complex dynamics as hundreds of cars are assembled with nonlinear couplings, carrying tens of thousands tons of freight and multiple locomotives distributed throughout the train. The longer the trains, the larger the control and optimization problem is, imposing difficulties in its solution, especially concerning computational time. Different train configurations present also various train handling problems and a number of techniques have been employed trying to control in-train forces properly.

In [65], an open loop scheduling optimal cruise control methodology taking into account operation safety is presented considering ECP brakes. In [25], an LQR minimizes coupler forces at the same time it maintains velocity tracking from reference values. Linear simplified models are adopted also in [60]. In [63] and [60], the model predictive control strategy is considered, aiming at the state dynamic prediction and try to act in advance avoiding breaking couplers but without loosing sight of a speed reference and fuel consumption. A discrete model is used to anticipate the system behavior for every admissible actuation sequence. Nonlinear model predictive control algorithms are also applicable [17], [24] in the context of the train handling problem.

1.4 Objective

The objective of this dissertation is to develop a simulator for the dynamics of heavy haul trains considering some of the involved nonlinearities, as well as to investigate the applicability of the Model Predictive Control methodology to manage the tradeoff among train handling, travel time and energy consumption using real train and track data.

1.5 Dissertation Outline

This dissertation is organized as follows: in Chapter 2, the train nonlinear model is presented, along with a proposed linear version. Then, it also shows the most relevant aspects of a real train and the Ferrovia do Aço track, simulation data from the operation is included as well. The main control challenge is presented in Chapter 3 and the numerical simulation results are described in Chapter 4. Finally, Chapter 5 presents the conclusions of this study and also gives some suggestions for further research.

Chapter 2

Train Dynamic Model and Track/Train Data

In this chapter a general train dynamic model is proposed for any number of cars, taking into account not only the whole train movement but also the in-train dynamics. A linear simplified model is suggested, approximating the nonlinear couplers dynamic behavior with a spring-damping scheme.

Then, available data of the *Ferrovia do Aço* track characteristics, along with a real train configuration is presented. Some data of the real operation simulator of a trip is also shown to illustrate the problem.

2.1 Nonlinear Model

In the following, a train with n connected cars ($n-1$ couplers) and m locomotives will be considered. Figure 2.1 illustrates the connection between cars in the middle of a train, with the relative displacement between the i-th and $(i+1)$-th cars being represented by x_{in_i}, where $i = 1, 2, ..., n$. As the lead is only connected to its successor and the last car is only connected to its predecessor, then $x_{in_0} = x_{in_n} = 0$.

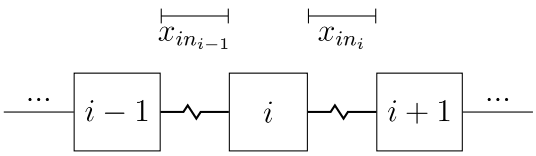

Figure 2.1 – Connected Cars in a Train.

The dynamic behavior of each connected car (wagon or locomotive) is then analyzed separately, as Figure 2.2 illustrates, with v_i and m_i being respectively the i_{th} car speed and mass. In addition, f_{in_i} is the in-train force between the i-th and $(i+1)$-th cars. Similarly, $f_{in_0} = f_{in_n} = 0$.

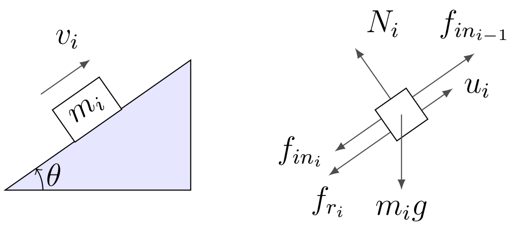

Figure 2.2 – Forces acting on a single car

$$m_i \dot{v}_i = u_i + f_{in_{i-1}} - f_{in_i} - f_{ext_i} \tag{2.1}$$

where

u_i is the traction/brake force for the i-th car;

f_{ext_i} is the resultant of external forces acting over each car.

From this, the dynamics in (2.1) is written, describing the relative movement of each car with respect to the next one in a connected train.

It shall be noticed that wagons are only capable of braking, which imposes $u_i < 0$ for every wagon, whereas the locomotives efforts are only bounded by its power characteristics as will be described in Section 2.3, being capable of providing tractive and dynamic braking efforts.

$$f_{in_i} = k_i\, x_{in_i} + b_i\, \dot{x}_{in_i} \tag{2.2}$$

where

k_i is the spring constant;

b_i is the linear damping coefficient, both from the i-th coupler.

In (2.1), it can be assumed that the inter-cars forces f_{in_i} and $f_{in_{i-1}}$ follow (2.2), although in general the couplers dynamics are more complex than this.

$$f_{ext} = f_{r_i} + f_{grav_i} \tag{2.3}$$

$$f_{grav_i} = m_i\, g\, sin(\theta_i) \tag{2.4}$$

where f_{grav_i} is the component of the gravity force affecting the car movement and θ_i is the terrain slope on the i_{th} car.

The resistance forces f_{r_i} represented in (2.3), can be modeled by (2.5):

$$f_{r_i} = m_i\,(c_{a_i} + c_{b_i}\,v_i + c_{c_i}\,v_i^2) \tag{2.5}$$

where c_{a_i}, c_{b_i} and c_{c_i} are each car drag davis coefficients. [59], [32].

Also, in (2.1), f_{ext_i} is the resultant of external forces acting over each car. As (2.3) states, these external forces are essentially drag forces (aerodynamic, ground resistance), represented in f_{r_i}, and also forces related to the terrain, due to the track slope and curvature although the latter is neglected in f_{grav_i}.

$$\bar{u_i} = u_i - \delta_i. \tag{2.6}$$

$$\delta_i = m_i\,(c_{a_i} + c_{c_i}\,v_i^2) + f_{grav_i} \tag{2.7}$$

Now, δ_i is defined in (2.7), in order to separate it from f_{ext} and consider a modified control variable given by (2.6).

$$\begin{aligned} m_i\dot{v_i} &= \bar{u_i} + k_{i-1}\,x_{in_{i-1}} + b_{i-1}\,\dot{x}_{in_{i-1}} - k_i\,x_{in_i} - b_i\,\dot{x}_{in_i} - m_i\,c_{b_i}\,v_i \\ \dot{x}_{in_i} &= v_i - v_{i+1} \end{aligned} \tag{2.8}$$

Then, combining (2.2), (2.3), (2.5) and (2.7) with the original dynamic (2.1), we can describe this system through (2.8). Finally, noting also that $\dot{x}_{in_i} = v_i - v_{i+1}$, a linear state space for this system is can be deduced.

2.2 Linear Model

Hereinafter, a state $x \in \mathbb{R}^{2n-1}$ is considered, consisting of each car speed v_i and also the relative displacement between cars x_{in}.

$$x = \left[v_1, ..., v_n, x_{in_1}, ..., x_{in_{n-1}}\right]^T \tag{2.9}$$

$$\begin{aligned} \dot{x} &= A\,x + B\,\bar{u} \\ y &= C\,x \end{aligned} \tag{2.10}$$

Then, (2.9) allows to write the system in the form of (2.10), with x given by (2.9) and $\bar{u} = \begin{bmatrix}\bar{u}_1, ..., \bar{u}_n\end{bmatrix}^T \in \mathbb{R}^n$.

where $A \in \mathbb{R}^{(2n-1)\times(2n-1)}$ and $B \in \mathbb{R}^{(2n-1)\times n}$:

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & 0_{(n-1)\times(n-1)} \end{bmatrix} \qquad B = \begin{bmatrix} B_{11} \\ 0_{(n-1)\times n} \end{bmatrix}$$

specifically, $B_{11} = diag\{m_1^{-1}, ..., m_n^{-1}\}$, $B_{11} \in \mathbb{R}^{n\times n}$ and

$$A_{11} = \begin{bmatrix} -(\frac{b_1}{m_1} + c_{b_1}) & \frac{b_1}{m_1} & 0 & \dots & 0 \\ \frac{b_1}{m_2} & -(\frac{b_1+b_2}{m_2} + c_{b_2}) & \frac{b_2}{m_2} & \ddots & \vdots \\ 0 & \ddots & \ddots & \ddots & 0 \\ \vdots & \ddots & \frac{b_{n-2}}{m_{n-1}} & -(\frac{b_{n-2}+b_{n-1}}{m_{n-1}} + c_{b_{n-1}}) & \frac{b_{n-1}}{m_{n-1}} \\ 0 & \dots & 0 & \frac{b_{n-1}}{m_n} & -(\frac{b_{n-1}}{m_n} + c_{b_n}) \end{bmatrix}$$

$$A_{21} = \begin{bmatrix} 1 & -1 & 0 & \dots & 0 \\ 0 & 1 & -1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & 1 & -1 \end{bmatrix} \qquad A_{12} = \begin{bmatrix} \frac{-k_1}{m_1} & 0 & \dots & 0 \\ \frac{k_1}{m_2} & \frac{-k_2}{m_2} & \ddots & \vdots \\ 0 & \ddots & \ddots & 0 \\ \vdots & \ddots & \frac{k_{n-2}}{m_{n-1}} & \frac{-k_{n-1}}{m_{n-1}} \\ 0 & \dots & 0 & \frac{k_{n-1}}{m_n} \end{bmatrix}$$

with $A_{11} \in \mathbb{R}^{n\times n}$, $A_{12} \in \mathbb{R}^{n\times(n-1)}$ and $A_{21} \in \mathbb{R}^{(n-1)\times n}$. In addition, we consider only the lead locomotive speed as measurement $\hat{y}$. Thus, $C = \begin{bmatrix}1 & 0 & \dots & 0\end{bmatrix}$, $C^T \in \mathbb{R}^{2n-1}$.

$$x[k+1] = \Phi\,x[k] + \Gamma\,\bar{u}[k] \tag{2.11}$$

$\Phi = e^{AT_s}$ and $\Gamma = \int_0^{T_s} e^{A\tau} B d\tau$ [63].

Then, this continuous time-domain state space is discretized with the zero order hold method and a sampling time of T_s, as represented in (2.11).

In Section 2.3, the *Ferrovia do Aço* track and a real train configuration are introduced.

2.3 Ferrovia do Aço Track and the MRS Train

In this section, we present a typical trip in the Ferrovia do Aço track with the MRS train. Real data presented in this chapter is from a real simulator currently used for this operation and was gently provided to enrich this work by MRS Logística S.A. The data collected was treated inside R studio, using the R language useful for treating large amounts of data [44].

The MRS train is led by two GE AC 44 locomotives, followed by 67 double wagons and more two equal locomotives in the rear of the train. In total, 138 vehicles are coupled together forming a train. Each double wagon has a rigid bar connecting single wagons as illustrated in Figure 2.3.

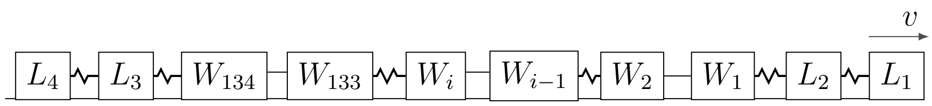

Figure 2.3 – MRS train representation

GE AC 44 are diesel electric locomotives with alternating current traction whose effort and braking curves are presented in Figures 2.4 and 2.5.

These locomotives allow the choice of eight different levels of power, represented by eight throttle positions, called notches. Notch 1 (N1) is the lowest level of power and notch 8 (N8) the highest. Similarly, there are eight power levels for the dynamic braking, with DB1 being the weakest brake and DB8 the highest one. Also, there exists an idle position where there is no tractive nor braking effort being employed by the locomotive. In total, there are seventeen power locomotive levels: DB8, DB7, DB6, DB5, DB4, DB3, DB2, DB1, N0, N1, N2, N3, N4, N5, N6, N7 and N8, called the locomotive notches.

The traction effort or brake that a locomotive is capable of applying into a train relies on the chosen throttle position, combined with the locomotive speed, as in Figures 2.4 and 2.5. From Figure 2.4, one can notice that, at low speeds, the tractive force is independent of the locomotive speed, being proportional to

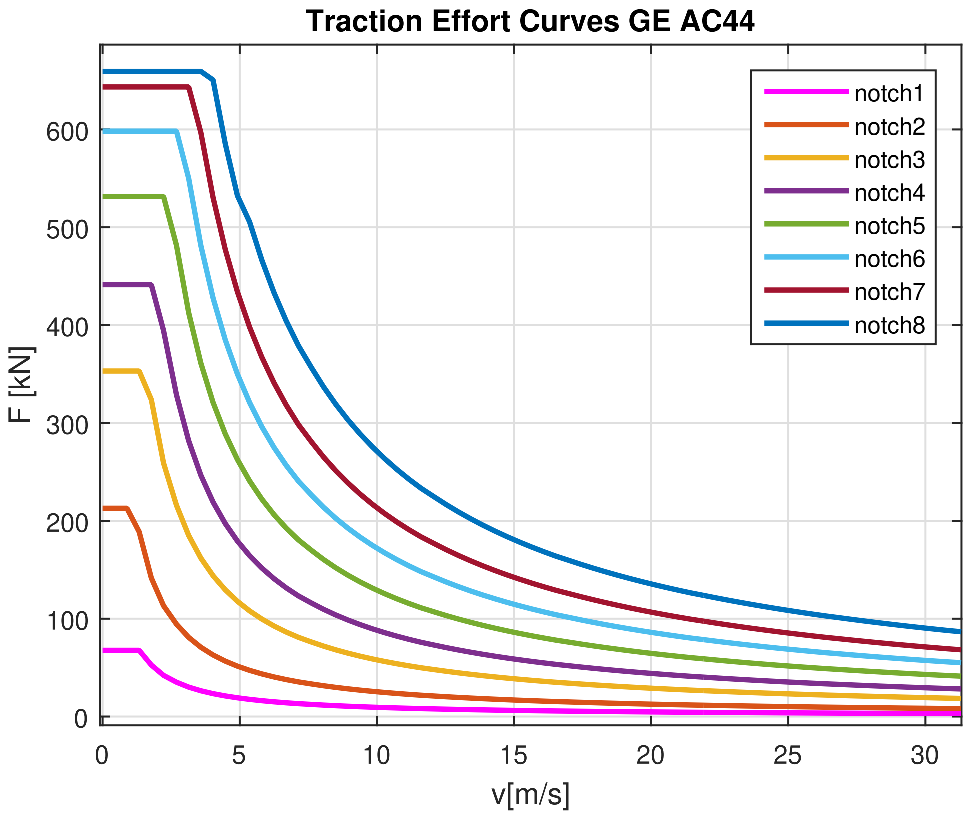

Figure 2.4 – GE AC44 Locomotive Traction Effort based on its speed and notch. *Data gently provided by MRS Logística.*

the notch position. On the hand, for higher speeds, the tractive effort available decreases as the locomotive speed increases.

From the ordinate scale in Figure 2.5, one can notice that locomotives dynamic brakes magnitudes are lower than the ones encountered for its tractive efforts.

2.3.1 Real Available Data of a Typical Trip

The Ferrovia do Aço elevation and angles are represented in Figure 2.6 from the city of Mariana, excerpt of the road known as the kilometer 293, in the State of Minas Gerais, until Saudade, which represents the kilometer zero in reality. For the simulation purpose though, as the train will run from Mariana to Saudade, in Figure 2.6, the abscissa is inverted: kilometer zero represents Mariana and kilometer 293 is located in Saudade, as will be reforced in Chapter 4.

MRS Logística S.A has gently provided one trip data from the simulator

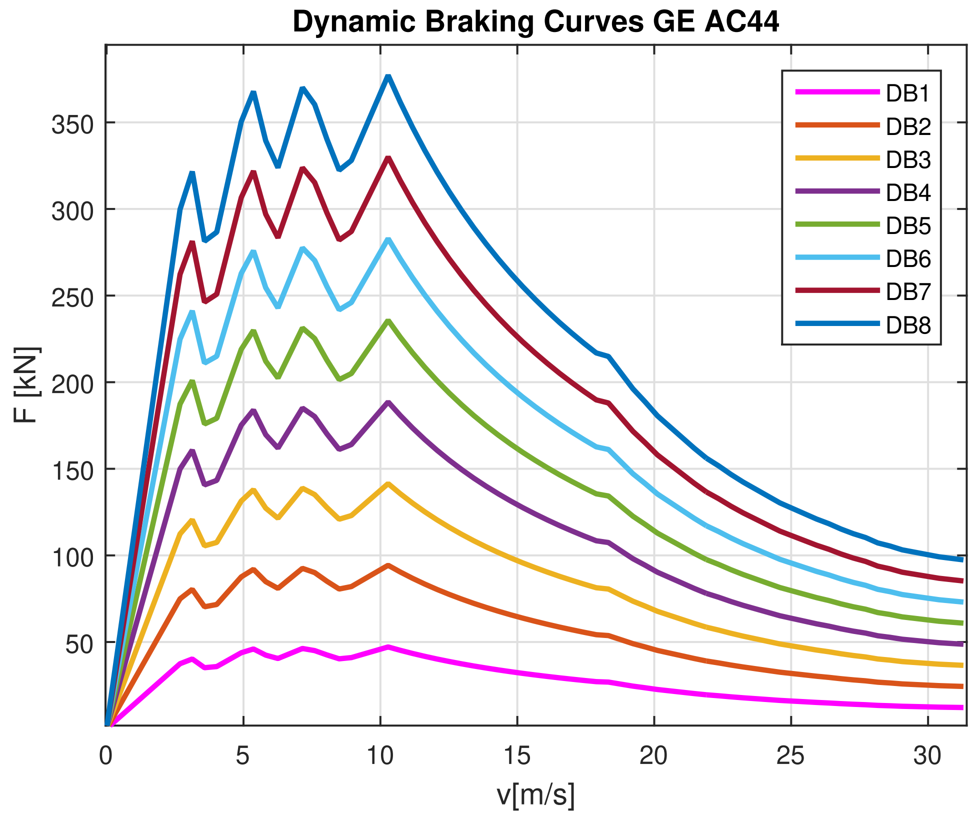

Figure 2.5 – GE AC44 Locomotive Dynamic Brake Effort based on its speed and notch. *Data gently provided by MRS Logística S.A.*

they currently have in operation. In this simulation data, their train takes around five hours and nine minutes in a 193 kilometer trip from Mariana in the direction of Saudade. Figure 2.7(a) presents first the train mean speed, i.e.: the mean of every car speed, in function of the lead locomotive position. The lead and remote notches and lead locomotive effort within the track are also represented in Figure 2.7.

In Figure 2.7, we notice the train startup from zero speed and back to stop at its final destination. During the track, the locomotives consists pass from synchronous operation to asynchronous notches and vice-versa in different segments. The lead consist assumes both tractive efforts and dynamic braking notches whereas the remote consist do not go into dynamic braking.

Also, the animation in Figure 2.8 shows the registered maximum steady and impact forces during this trip. Each frame represent one kilometer in the referred travel: every force collected data inside the same trip kilometer is represented in the same snapshot. Thus, every blue point represent the maximum draft steady force encountered for different time instants, in which data was collected. Its abscissa

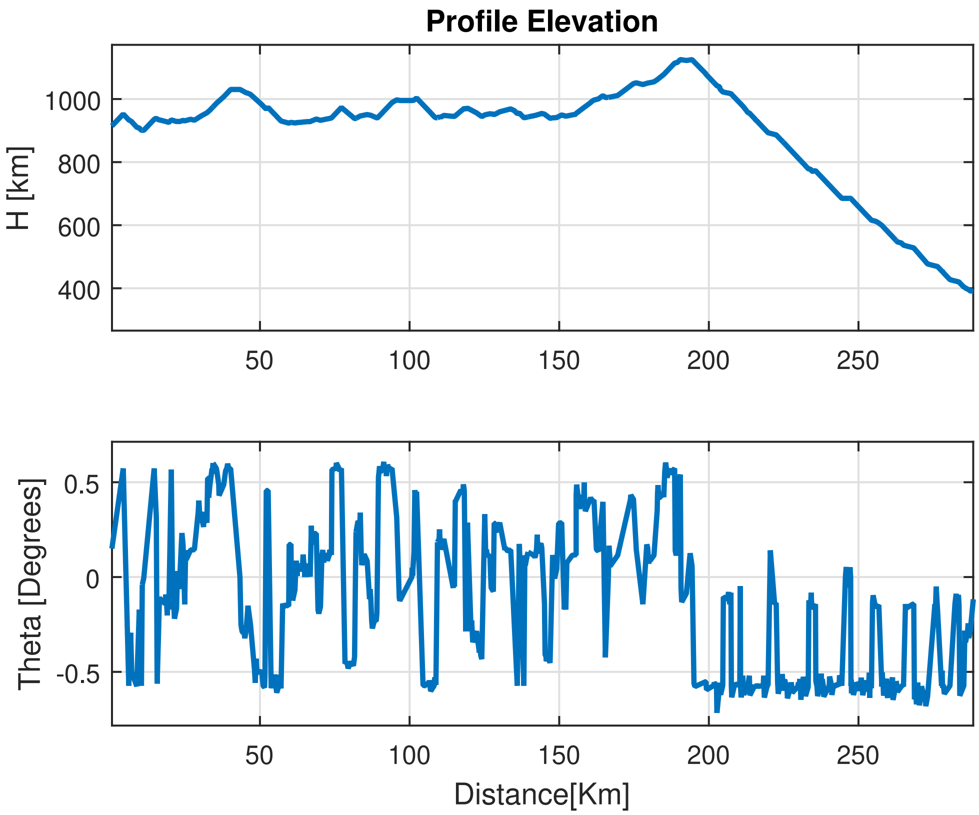

Figure 2.6 – Ferrovia do Aço Elevation and angles. *Data gently provided by MRS Logística S.A.*

is the corresponding coupler of this occurrence inside of the train. Similarly, red points are the maximum buff forces, with its respective couplers in the x-axis. Finally, black points are the impact forces, including run-ins and run-outs along the train.

Given this representation of the real forces extracted from the operation simulator, in the animation frames, sometimes blue and red lines are present, as in the first animation frames. A line of vertical points means that, in a given kilometer, a certain number of maximum forces inside the train were registered for the same coupler. In the trip startup, it happens usually in couplers adjacent to the locomotives as they are imposing the traction effort needed to move the train from the inertia. On the other hand, horizontally spread points interpretation is related to the forces waves traveling throughout the train couplers as the maximum forces occur sequentially along the train. Note also that steady forces have a higher magnitude than impact forces (the transient ones).

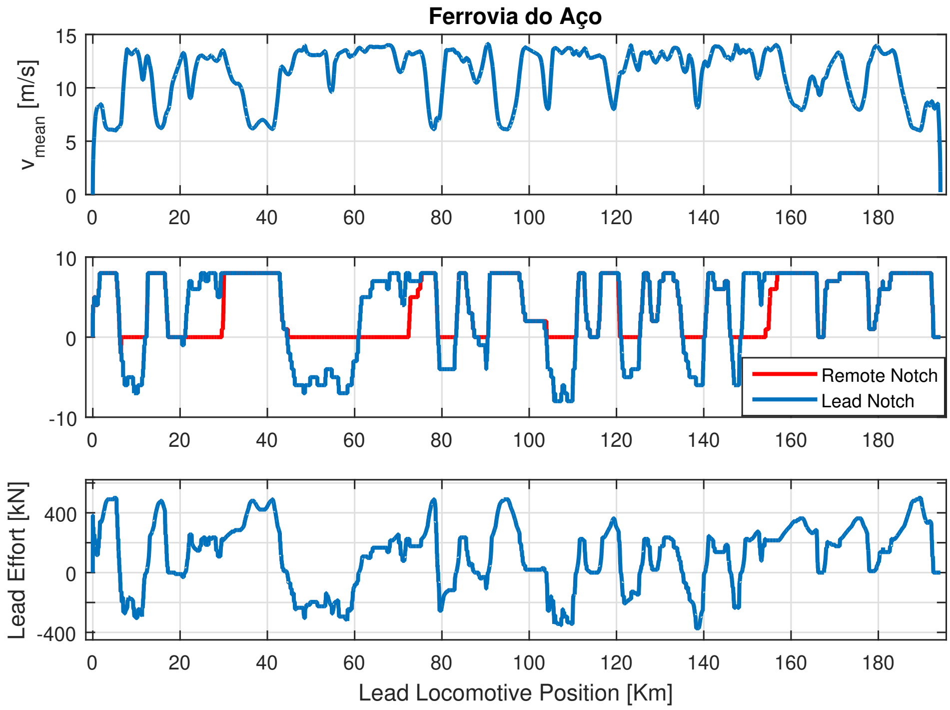

Figure 2.7 – (a) Train mean speed [m/s] (b) Lead and remote locomotives notches (c) lead locomotive effort [kN] in function of the lead locomotive position *Data gently provided by MRS Logística S.A.*

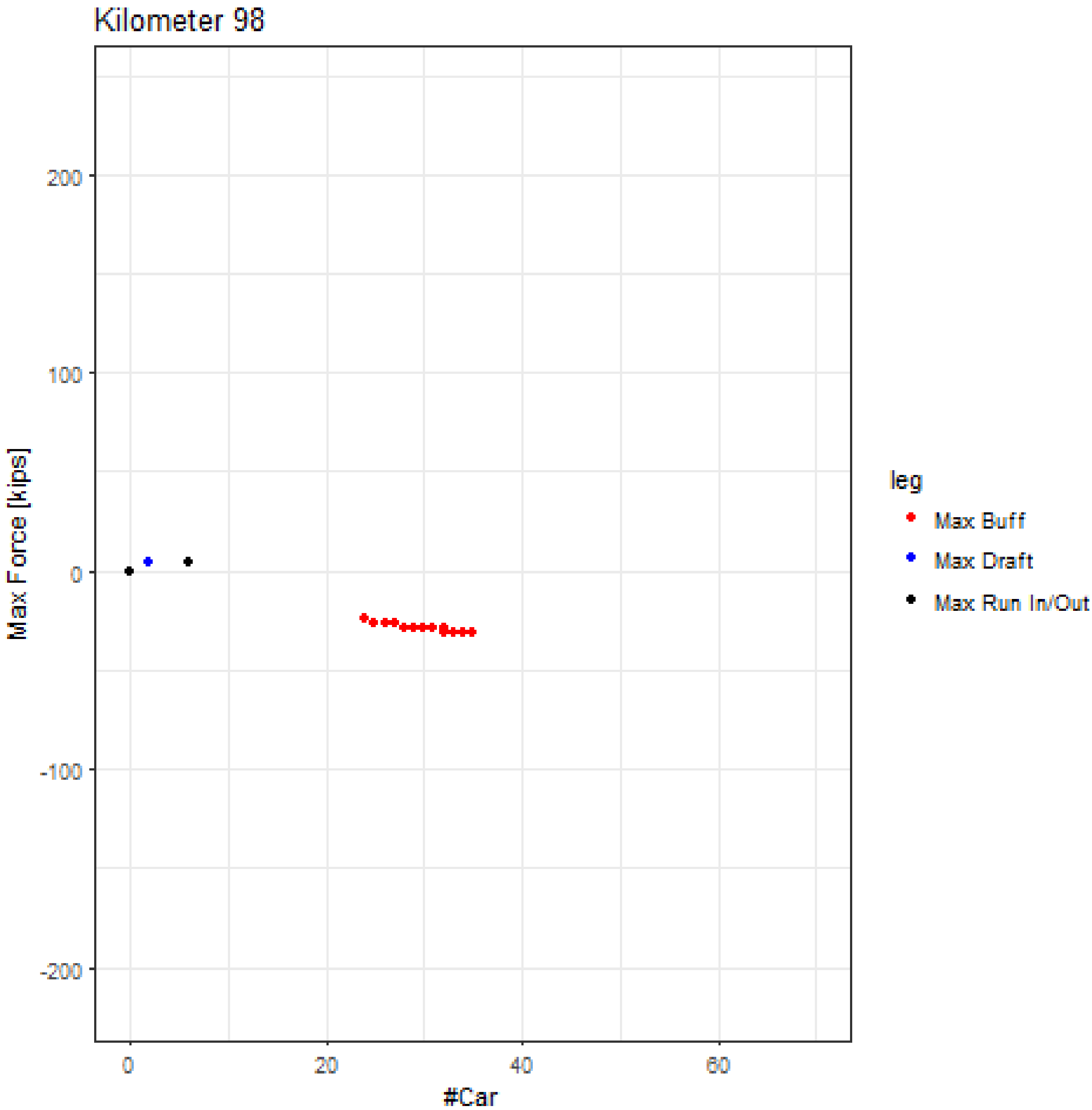

Figure 2.8 – Train steady and impact forces in the Ferrovia do Aço Track *Data gently provided by MRS Logística S.A*

Chapter 3

Model Predictive Control

Model Predictive Control (MPC) is a promising optimal control strategy that proposes the use of a dynamical model of the process to predict its evolution and choose the best control action [13], [56], [39],[46],[16]. For this, the control and state variables are concatenated to form an augmented prediction model, which can be multivariable, time-varying, with delays and disturbances. A simplified model would then anticipate the likely dynamic evolution and choose the control action accordingly [10].

Also, Model Predictive Control can be seen as an implementation of the Dynamic Programming (DP) solution, yielding a receding horizon control law although a DP solution might be difficult to obtain if the state dimension is considerably high [46]. MPC may also be considered to solve open loop optimal control problems. In this work, though, we study the MPC in its closed loop form, having in mind the model uncertainties, but considering that the complete state is known.

Despite the simplicity of this latter assumption for practical purposes, when the state must be estimated, the estimation associated error makes the future trajectory not precisely predicted. Thus, the optimal cost function minimization, on which the proof of stability is founded, relies on the assumption that the global solution can be computed based on the exact state anticipation.

In general, this optimal control strategy considers a quadratic cost function in the form of (3.1) similarly to the one of a Linear Quadratic Regulator. In fact, an infinite horizon unconstrained offline MPC is equivalent to an LQR [9],[46]. However, Model Predictive Control is advantageous for constraint handling as it can compute the optimal trajectory already taking into account input, output and state constraints.

Besides, in a finite horizon scheme, the control action can be determined online at each sampling instant by moving the horizon sequentially and considering the new initial state as the current state. A finite sequence of controls is obtained and, in a classical MPC scheme, only the first control action is effectively applied to the plant before moving the window and the rest of the sequence is ignored. When the next time interval is taken into account, a more recent state of the model is considered to calculate the new feedback controller gain. As it becomes clear in this procedure, the moving horizon scheme computes a time variant feedback controller gain as opposed to the infinite horizon case.

The tunning parameters are the same Q and R matrices from the LQR regulator plus the horizon size. It is important to keep in mind that the controller tries to find a gain to minimize the cost function J in (3.1). That means its action will be focused on the highest term in the sum represented in the integral.

Thus, if one specific variable is meant to remain small over time, it is reasonable to choose a high coefficient for it so that the solver will work on the corresponding parcel. Nevertheless, each coefficient has its influence in the others in the sense of the criteria, which means that it is the relative value of the weights in comparison with others that will overall catch the solver's attention. Variables normalization is a key factor in that sense, in order to have a clear idea of the real priority given to each in the tunning methodology.

Therefore, increasing Q/R weights will penalize more the corresponding state/control. The described tunning logic works for each sampling instant. However, for the finite horizon Model Predictive Control, the overall objective function is summed over all sampling instants inside the referred window.

In other words, the cost function to be minimized is composed of more than one term of the form of (3.1). One individual parcel can be higher in the whole sum if compared to other sampling instants. In that sense, the size of horizon also becomes an important tunning parameter.

Indeed, short horizons will certainly imply an increased number of windows to be considered in the same trajectory optimization although the computational time in each of them is reduced as the decision variable size is shorter. A shorter horizon will surely prioritize the optimization in the short term as it considers less parcels of the form of (3.1) in the overall cost function. On the other hand, a drawback of this choice is that it can limit the state prediction capacity and the calculated control action to be applied will have limited influence in long term time samplings.

Depending on the actuator limits, though, it might be necessary to consider acting in advance to achieve the desired performance in the medium/long terms with higher time prediction and correction capacity even if it might mean abdicating better results in the immediate next sampling instants. As one can imagine, less windows would be taken into account in this case at the price of a longer computational time in each, although not necessarily in the overall scheme.

Indeed, the increase in the optimization horizon implies in an augmented problem scale and difficulties also arise in handling the overall objective function behavior in terms of local minima for example, possibly imposing also the need for good initial guesses. A prediction horizon N_p can also be distinguished from a control horizon N_c in the MPC literature although it is considered just one $N = N_c = N_p$ in this dissertation.

The model predictive control technique was firstly employed back in the seventies for process control due to its longs time constants but it is now widespread among the automotive industry, aerospace and unmanned aerial vehicles, information and communication technologies, energy, finance and industrial productions.

In the railroad, the MPC has also been already studied in the context of automatic train operation (ATO) [58] and for trajectory planning of multiple high speed train movements [61]. In [64], the MPC is investigated in the context of finding an optimal application of the fence methodology in distributed power trains with mid consists. To manage the trade-off among coupler forces, trajectory tracking and energy consumption as proposed in this dissertation, [63] presents the closest developed approach.

3.1 Optimization Control Problem

The MPC performance index of interest for this application is represented (see also [63]), highlighting the trade off among train handling, fuel (energy) consumption and speed tracking:

$$J = \int_{t_0}^{t_f} (\sum_{i=1}^{n-1} K_f f_{in}^2 + \sum_{i=1}^{n-1} K_u u_i^2 + \sum_{i=1}^{n-1} K_v (v_i - v_r)^2) dt \tag{3.1}$$

where n is the number of cars, v_r is the plan reference speed to be tracked, t_0 and t_f define the time interval the cost function (3.1) is applied to. Besides, $K_f[1/N^2]$,$K_v[1/(m/s^2)^2]$ and $K_u[1/N^2]$ penalize the in-train forces, the reference speed tracking and the energy consumption respectively.

Note that, if every car follows the reference speed as the optimal cost function

(3.1) imposes, then there is no relative speed and displacement between cars and coupler forces are handled.

Also, energy minimization is actually represented by the integral of power, i.e: the product of the cars effort u_i and speed v_i. As there is already a term to track the predefined plan speed, the effort u_i is included for the energy minimization purpose instead of the power itself [63].

Rewriting (3.1) to consider the linear state space in (2.9), one can obtain:

$$J = \int_{t_0}^{t_f} (x^T Q x + u'^T R u' + F_1^T x + F_2^T u') dt \tag{3.2}$$

where

$$\begin{aligned} Q &= K_f Q_f + K_v Q_v \\ Q_f &= L L^T \end{aligned}$$

$$L = \begin{bmatrix} b_1 & -b_1 & 0 & k_1 & 0 & \dots & 0 \\ 0 & b_2 & -b_2 & 0 & k_2 & 0 & \vdots \\ \vdots & \dots & \ddots & \ddots & \dots & \ddots & 0 \\ 0 & \dots & 0 & b_{n-1} & -b_{n-1} & 0 & k_{n-1} \end{bmatrix} \quad Q_v = \begin{bmatrix} I_n & 0_{n\times(n-1)} \\ 0_{(n-1)\times n} & 0_{(n-1)\times(n-1)} \end{bmatrix}$$

with $R = K_e I_n$, $F_1^T = -2K_v v_r I_{ss}$, $F_2^T = 2K_e \begin{bmatrix}\delta_1, ..., \delta_n\end{bmatrix}$, I_n is a n-size identity matrix and $I_{ss} = \begin{bmatrix} I_v & I_{x_{in}} \end{bmatrix}^T \in \mathbb{R}^{2n-1}$, with $I_v = \begin{bmatrix}1, ..., 1\end{bmatrix}^T \in \mathbb{R}^n$ and $I_{x_{in}} = \begin{bmatrix}0, ..., 0\end{bmatrix}^T \in \mathbb{R}^{n-1}$.

The considered constraints are the upper and lower bounds on the control signal, i.e., the locomotives tractive effort and dynamic braking as well as the wagons air braking. Note that the wagons are only capable of braking, so the wagons upper bound effort is already limited at zero by definition.

$$u_i^l \leq \bar{u} + \delta_i \leq u_i^u, \qquad i = 1, 2, ..., n \tag{3.3}$$

$$f^l \leq f_{in_k} \leq f^u, \quad k = 1, 2, ..., n-1 \tag{3.4}$$

As the decision variable for the formulated problem is the $\bar{u}$ as in (2.7), in order to design our controller satisfying these constraints, the actual control constraints are transformed as (3.3) to account for δ_i deviations.

Considering that the main objective of this work is to achieve performance improvements in terms of train handling, one could think of including in-train forces constraints, as the adjacent car forces can be expressed as a function of the state as in (2.2). Then, considering upper and lower limits for these forces, (3.4) can be derived.

The more restrictions are added, the greater the dimension of the optimization problem for the solver to handle. In this case, for each sampling instant, $(2n-1)$ constraints are active.

The optimization control problem formulation for each sampling instant is then to optimize (3.1) satisfying (2.10) subject to (3.3) and, possibly, (3.4), as we shall discuss later.

3.2 Augmented State Space for the Optimization Horizon

The augmented state space considering the horizon N is represented.

$$X = Fx(k_c) + \Theta U \tag{3.5}$$

where $x(k_c)$ is the current state in the beginning of the referred horizon, U is the control vector for the window and the decision variable for the optimization procedure. Also,

$$F = \begin{bmatrix} A \\ A^2 \\ A^3 \\ \vdots \\ A^N \end{bmatrix} \quad \Theta = \begin{bmatrix} B & 0 & \dots & 0 \\ AB & B & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ A^2B & AB & \dots & 0 \\ A^{N-1}B & A^{N-2}B & \dots & B \end{bmatrix} \tag{3.6}$$

The corresponding matrices dimensions are $F \in \mathbb{R}^{N(2n-1)\times(2n-1)}$, $\Theta \in \mathbb{R}^{N(2n-1)\times nN}$ and

$$X = \begin{bmatrix} x(k_c+1) & x(k_c+2) & \ldots & x(k_c+N) \end{bmatrix}^T \in \mathbb{R}^{N(2n-1)}, \tag{3.7}$$
$$U = \begin{bmatrix} \bar{u}(k_c) & \bar{u}(k_c+1) & \ldots & \bar{u}(k_c+N-1) \end{bmatrix}^T \in \mathbb{R}^{nN}. \tag{3.8}$$

3.3 MPC Constraints

In order to assure the constraints in (3.3) and (3.4) for all the optimization horizon, it would be necessary to consider the augmented state space for the whole window.

For that purpose, to satisfy (3.4), the vector F_{in_i} is defined containing every in-train force on the i_{th} coupler for the horizon N: $F_{in_i} = \begin{bmatrix} f_{in_i}(k_c+1|k_c) & f_{in_i}(k_c+2|k_c) & \ldots & f_{in_i}(k_c+N|k_c) \end{bmatrix}^T$.

We also consider the state space variables from (2.9) on the horizon inside respective vectors, i.e: $X = \begin{bmatrix} V_{in} & X_{in} \end{bmatrix}^T$, where

$$\begin{aligned} X_{in_i} &= \begin{bmatrix} x_{in_i}(k_c+1|k_c) & x_{in_i}(k_c+2|k_c) & \ldots & x_{in_i}(k_c+N|k_c) \end{bmatrix}^T \\ V_{in_i} &= \begin{bmatrix} v_{in_i}(k_c+1|k_c) & v_{in_i}(k_c+2|k_c) & \ldots & v_{in_i}(k_c+N|k_c) \end{bmatrix}^T \end{aligned} \tag{3.9}$$

Therefore, $F_{in_i} = KX_{in_i} + BV_{in_i}$, with K and B being the augmented corresponding spring constant and damping vectors.

In other words, for the forces constraints, one should consider satisfying the in-train forces upper and lower bounds in the whole horizon:

$$F^l_{in_i} \leq KX_{in_i} + BV_{in_i} \leq F^u_{in_i} \tag{3.10}$$

We then define the matrices Zx, ZX, Zv and ZV to extract correspondingly X_{in} and V_{in} from the augmented state space in 3.5. The matrix $D_\delta \in \mathbb{R}^{n\times n}$ is also defined to obtain the cars relative speed performing the difference in cars speeds from the state space 2.10.

$$
\begin{aligned}
x_{in} &= Z_x x(k) \\
X_{in} &= Z_X X \\
v_{in} &= D_\delta Z_v x(k) \\
V_{in} &= D_\delta Z_V X
\end{aligned}
\tag{3.11}
$$

where

$$
D_\delta = \begin{bmatrix} 1 & -1 & 0 & \dots & 0 \\ 0 & 1 & -1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & 1 & -1 \end{bmatrix}
$$

$$
\begin{aligned}
Z_x &= \begin{bmatrix} 0_{(n-1)\times n} & I_{(n-1)\times(n-1)} \end{bmatrix} \\
Z_v &= \begin{bmatrix} I_{n\times n} & 0_{n\times(n-1)} \end{bmatrix} \\
Z_X &= \begin{bmatrix} Z_x & \dots & Z_x \end{bmatrix} \\
Z_V &= \begin{bmatrix} Z_v & \dots & Z_v \end{bmatrix}
\end{aligned}
$$

$Z_X \in \mathbb{R}^{N(n-1)\times N(2n-1)}$ and $Z_V \in \mathbb{R}^{nN\times N(2n-1)}$

With the set of equations defined in (3.11), we can write

$$
\begin{aligned}
X_{in} &= F_x x(k_c) + \Theta_x U \\
V_{in} &= F_v x(k_c)_+ \Theta_v U
\end{aligned}
\tag{3.12}
$$

where

$$\begin{aligned}
F_x &= Z_x F, \in \mathbb{R}^{N(n-1)\times(2n-1)} \\
F_v &= Z_v F, \in \mathbb{R}^{nN\times(2n-1)} \\
\Theta_x &= Z_x \Theta, \in \mathbb{R}^{N(n-1)\times Nn} \\
\Theta_v &= Z_v \Theta, \in \mathbb{R}^{nN\times Nn}
\end{aligned} \tag{3.13}$$

Rewriting (3.10) with the set defined in (3.13):

$$F_{in}^l \leq K(F_x x(k_c) + \Theta_x U) + BD_\delta(F_v x(k_c)_+ \Theta_v U) \leq F_{in}^u$$

becomes

$$F_{in}^l \leq (KF_x + BD_\delta F_v)x(k_c) + (K\Theta_x + BD_\delta \Theta_v)U \leq F_{in}^u$$

Taking this equation in the form of a decision variable inequality constraint:

$$M_r U \leq \gamma \tag{3.14}$$

where

$$M_r = \begin{bmatrix} (K\Theta_x + BD_\delta \Theta_v) \\ -(K\Theta_x + BD_\delta \Theta_v) \end{bmatrix} \gamma = \begin{bmatrix} F_{in}^u - (KF_x + BD_\delta F_v)x(k_c) \\ F_{in}^l + (KF_x + BD_\delta F_v)x(k_c) \end{bmatrix}$$

Nevertheless, if these in-train forces constraints are considered, the upper and lower limits F_{in}^l and F_{in}^u should be carefully chosen for each track-train configuration in combination with the horizon N selected. They should be designed as a really prohibitive condition to represent a true restriction, as the objective function already accounts for the desired reduction in forces magnitudes.

If too strict constraints are applied, it might be the case that, for a given initial condition inside the selected horizon, the solver will not be able to find a feasible solution because the forces magnitude set is not attainable.

The Model Predictive Control optimization problem is then to compute the future state trajectory behavior (3.7) resulting from the application of the control determined by the decision variable in (3.8), optimizing the objective function (3.1) summed over the whole horizon.

The optimization problem is solved with the quadprog solver inside MATLAB® and the simulations results are presented in the next chapter.

Chapter 4

Numerical Simulations

This chapter presents the numerical simulations performed with real track data provided by *MRS Logística*. The terrain geometry is illustrated in Figures 4.1 and Figure 4.2. The former present track elevation while the slopes are shown in the latter.

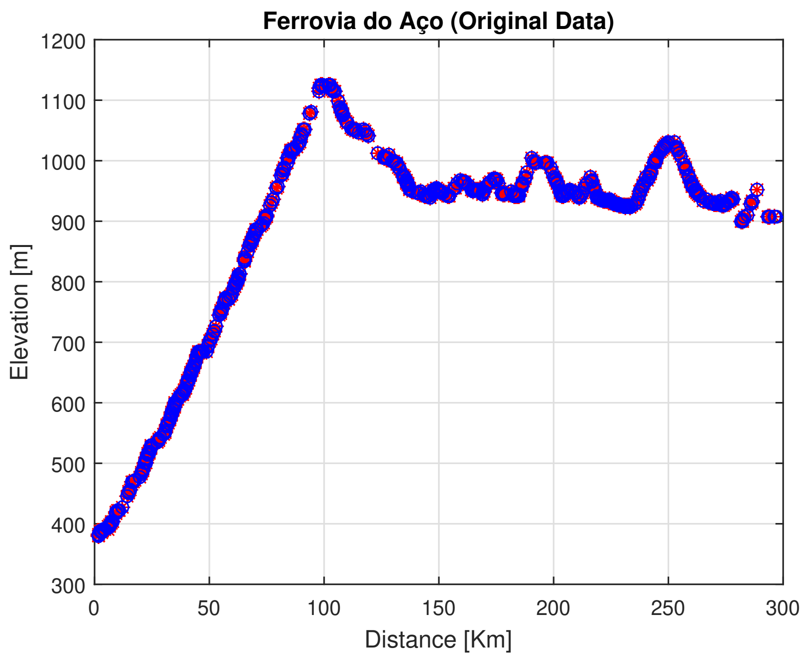

Figure 4.1 – Experimental data. The terrain elevation (h) of the terrain as a function of the track distance (s).

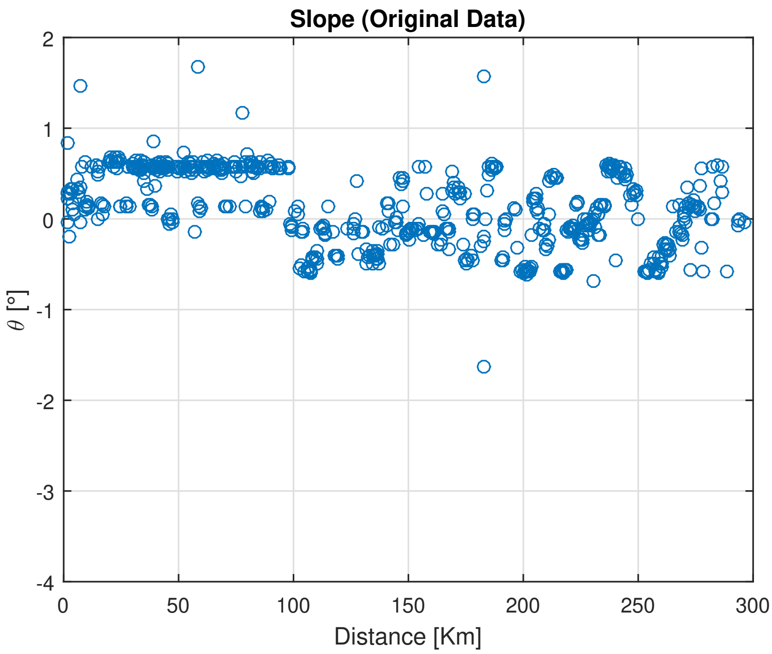

Figure 4.2 – Experimental data. The slope (θ) of the terrain as a function of the track distance (s).

In the real experimental data, the train starts to move from the track distance labeled as kilometer 293 to the one known as kilometer zero. For simulation purposes, the original data had to be reflected so that track data could be treated as monotonically increasing in the developed simulator, see Figures 4.3 and 4.4.

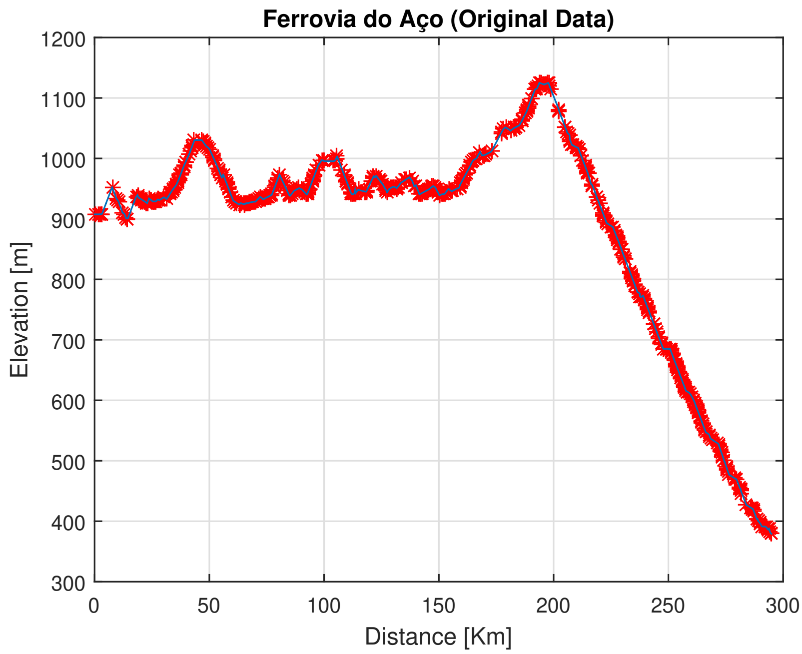

Figure 4.3 – Experimental data. The terrain elevation (h) as a function of the track distance (s), reflected for simulation purposes.

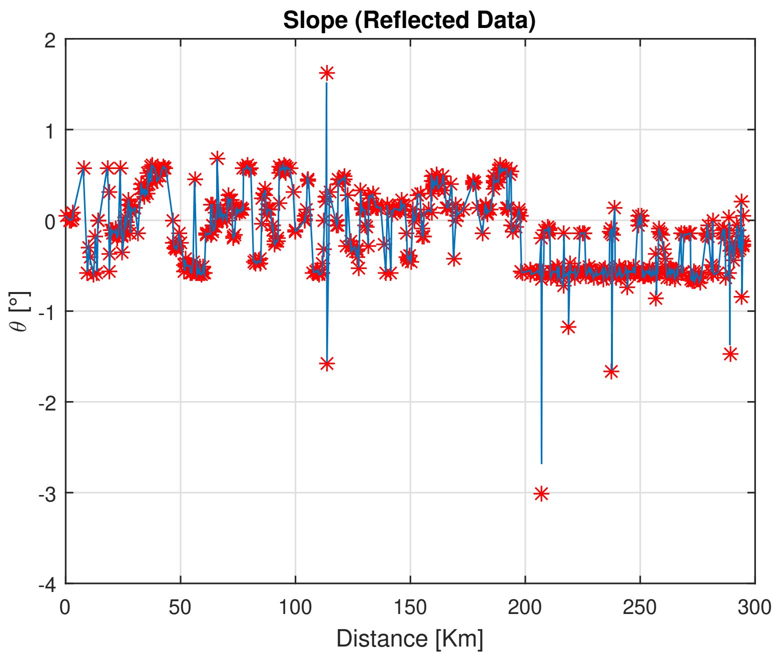

Figure 4.4 – Experimental data. The terrain slope (θ) as a function of the track distance (s), reflected for simulation purposes.

A record of one Ferrovia do Aço trip experimental data from the operations simulator, provided gently by *MRS Logística*, is also presented. The mean value of the whole train speed recorded in one the trip is illustrated in Figure 4.5. In the simulations performed in this work, the real train mean speed is assumed to be the reference speed to be tracked.

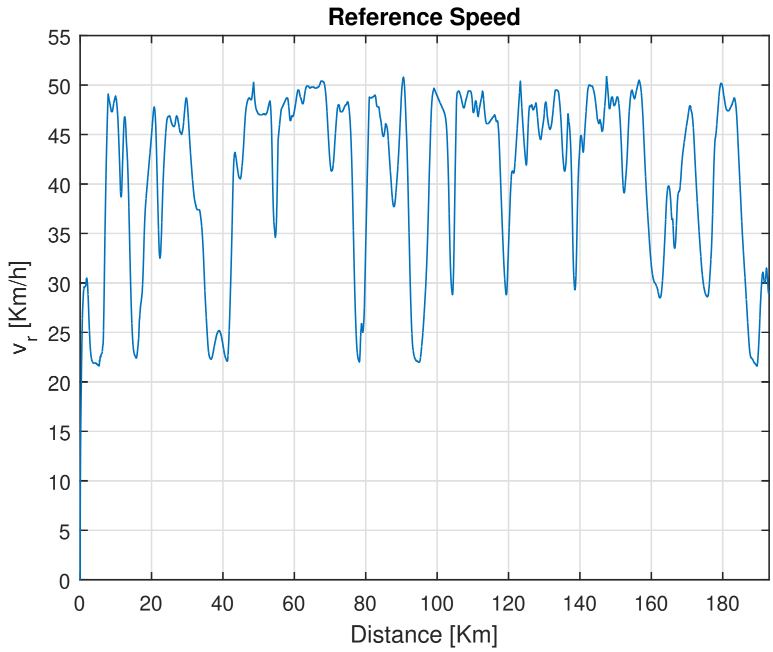

Figure 4.5 – Experimental data. Mean value of the train speed as a function of the lead locomotive position (p). The assumed reference speed plan.

The recorded lead locomotive gravity forces due to the terrain geometry are illustrated in Figure 4.6.

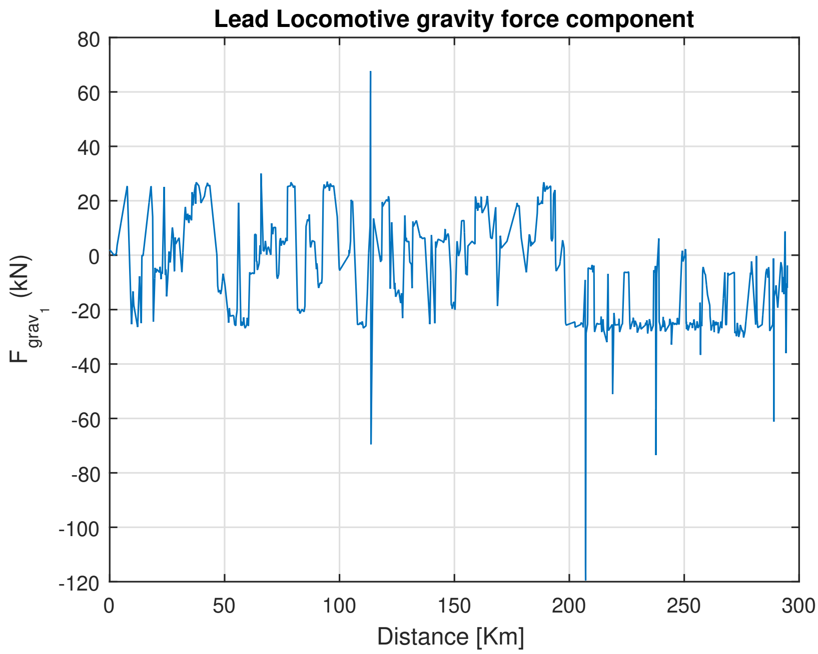

Figure 4.6 – Experimental data. The projection of the gravity force in the lead locomotive plan of movement as a function of its position p.

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4.1 Speed Tracking Controller

In order to illustrate the applicability of the chosen strategy, we consider the linear system (2.10), with a change in the control as in (2.6) to account for the presence of the nonlinear term F_p in (2.7) due to the terrain slope.

The coupler stiffness coefficient considered is $K_s = 4.2 \times 10^6$ (Nm/rad) and the damping coefficient $B = 1 \times 10^6$ $(Nm/rad/s)$ were obtained from [63],[60]. The wagons length $L_w = 52.6280$ (m) and mass $m_w = 260 \times 10^3$ (kg) are the same as in real MRS operation. The locomotive length $L_l = 22.3$ (m) and mass $m_l = 195 \times 10^3$ (kg) are taken from GE 44 locomotive public data. The total train mass $M = \begin{bmatrix} m_l & m_w & m_w & \dots & m_w \end{bmatrix}^T$ is then available to evaluate the model forces.

First, a conventional train is considered with no remote locomotive. The first train configuration considered is composed of a lead locomotive and 14 wagons. The state initial condition is: $x(0) = \begin{bmatrix} 0 & \dots & 0 \end{bmatrix}^T$ and the step size for the numerical simulation was of 0.1 with the Euler integration method.

For academic purposes, wagons air brakes were neglected and, in the first simulations, a flat terrain is imposed in order to illustrate later the relevance of gravity forces. In addition, we did not use the operational notches in Figure 2.7 but instead a simple proportional speed controller was implemented after feedback linearization to assure the lead locomotive is able to track the proposed reference signal. The proportional gain was $k_p = 10000$.

One can verify from Figure 4.7 that the lead locomotive tracks successfully the first desired constant velocity $v_r = 30$ Km/h. The train cars also follow the lead locomotive. Since the terrain is flat, in-train forces in Figure 4.8 appear to be more significant during the transient, i.e, taking the train from inertia to the desired movement, and a considerable coupler forces reduction is observed in steady state. Figure 4.9 illustrates the corresponding the lead locomotive tractive effort.

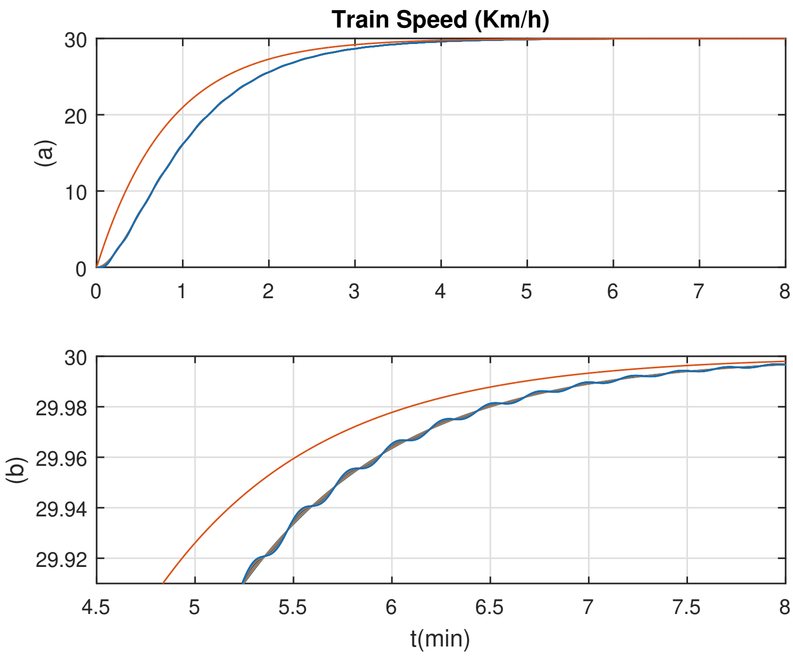

Figure 4.7 – Simulation results of a 15 cars train with a flat terrain. The time history of the train cars speed. A simple proportional speed controller with feedback linearization is applied in the lead locomotive. A constant speed reference is considered.

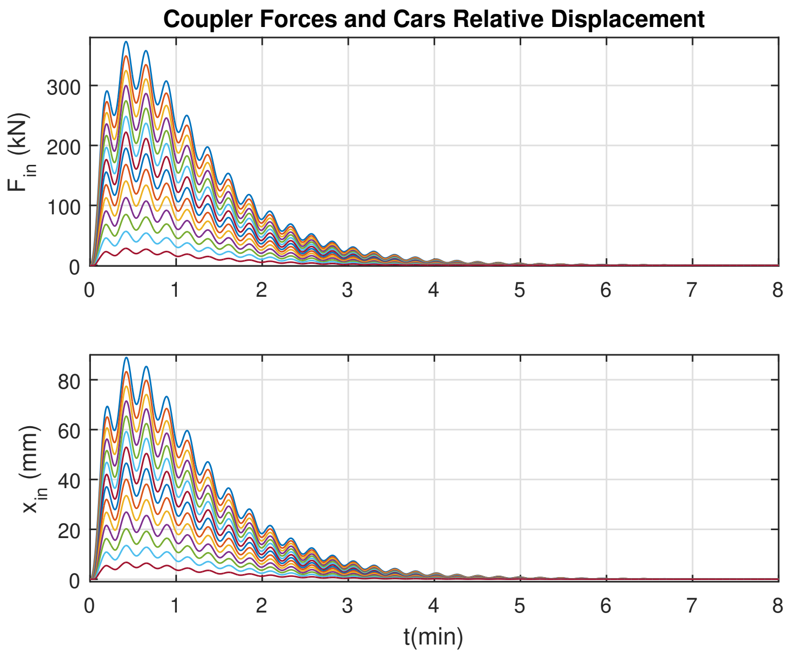

Figure 4.8 – Simulation results with 15 cars and a flat terrain. The couplers forces time history. A simple proportional speed controller with feedback linearization is applied on the lead locomotive.

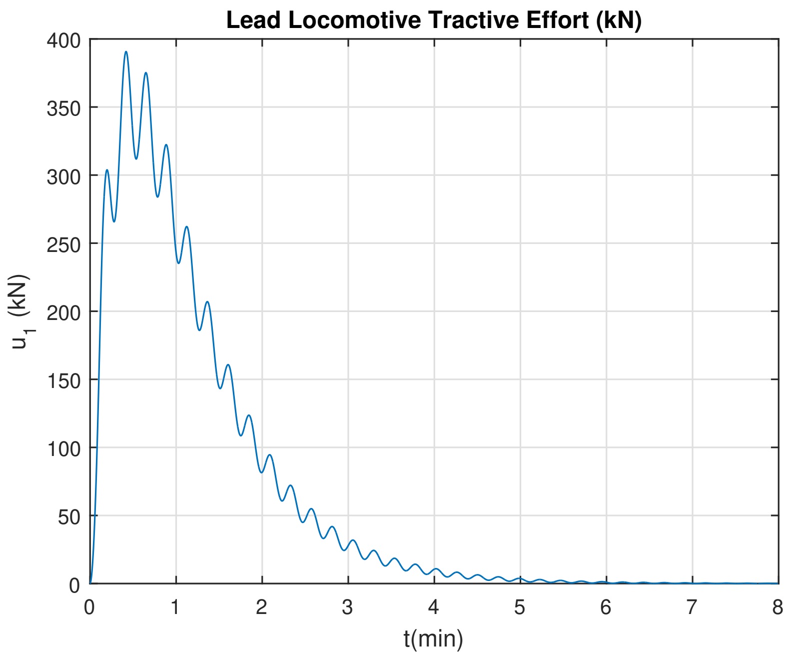

Figure 4.9 – Simulation results of 15 cars train and a flat terrain. A simple proportional speed controller with feedback linearization is applied on the lead locomotive.

Notice that, due to the large coupler stiffness and damping coefficients, small deviations in cars speed and relative displacement implies in significant in-train forces, as illustrated in Figure 4.8. The cars position are given in Figure 4.10.

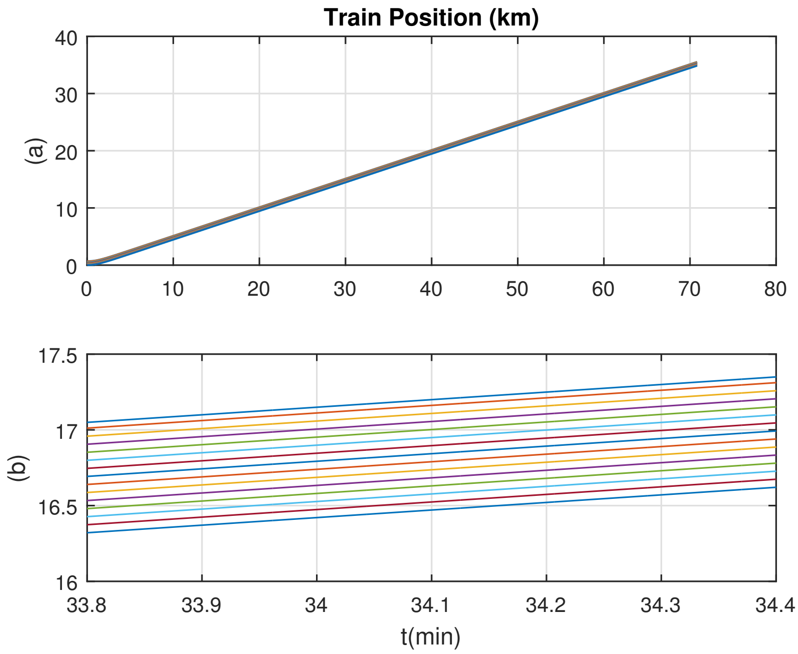

Figure 4.10 – Simulation results with 15 cars train and a flat terrain. The train cars position time history. A simple proportional speed controller with feedback linearization is applied on the lead locomotive.

Now, including the terrain real data (instead of considering a flat terrain), one can verify from Figure 4.11 that the couplers forces increase since the components of gravity forces in Figure 2.2 due to the terrain elevation and slope are now affecting the train dynamics intensively. Even a slope of 5°, which corresponds to a grade of around 1%, is already significant when regarding coupler forces magnitude. In this case, only the gravity force applied to the lead locomotive is completely canceled in the feedback linearization control law.

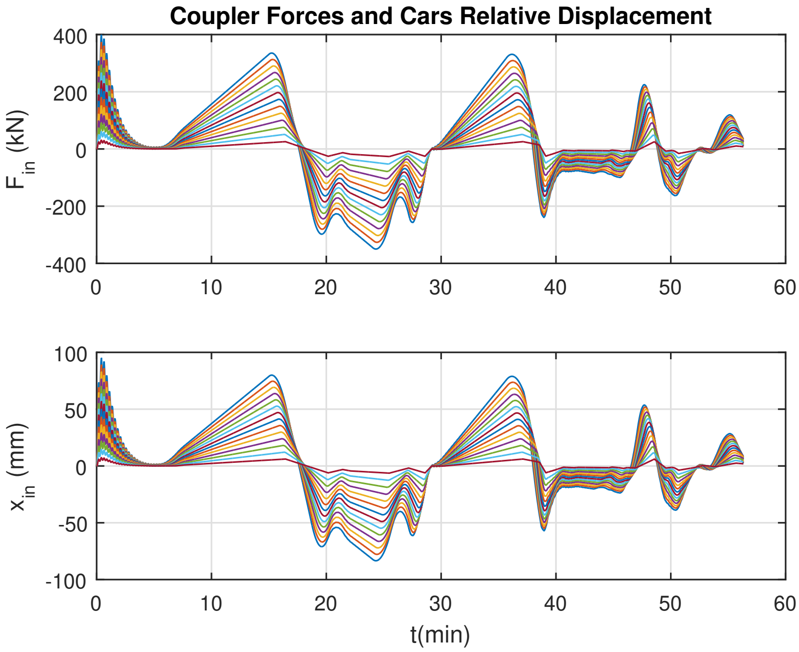

Figure 4.11 – Simulation results of a 15 cars train in the Ferrovia do Aço terrain. The coupler forces time history. A simple proportional speed controller with feedback linearization is applied on the lead locomotive.

The gravity forces in the lead locomotive are given in Figure 4.12 for this case.

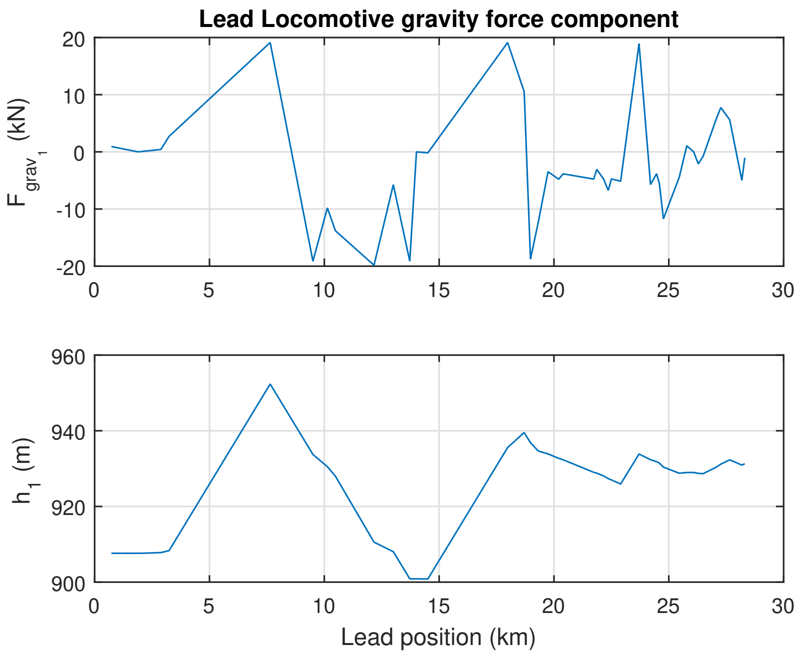

Figure 4.12 – Simulation results of a 15 cars train with the real terrain. The gravity forces in the lead locomotive due to the terrain geometry. A simple proportional speed controller with feedback linearization is applied on the lead locomotive.

One can also verify from Figure 4.13 that the lead locomotive tracks the desired constant speed and the train position time evolution is given in Figure 4.14 illustrating that the whole train follows the lead locomotive as expected.

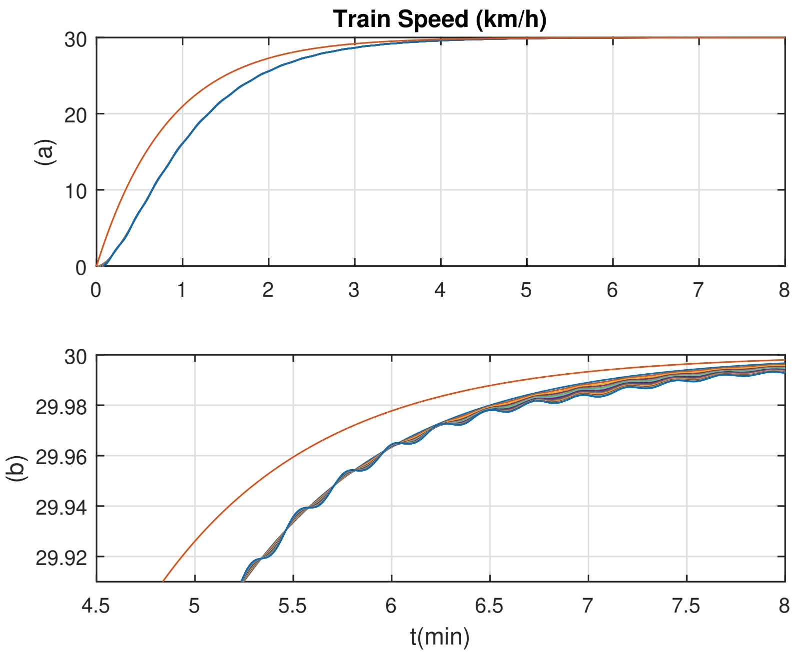

Figure 4.13 – Simulation results of a 15 cars train with the real terrain. The train cars speed time history. A simple proportional speed controller with feedback linearization is applied on the lead locomotive. A constant speed reference signal is considered.

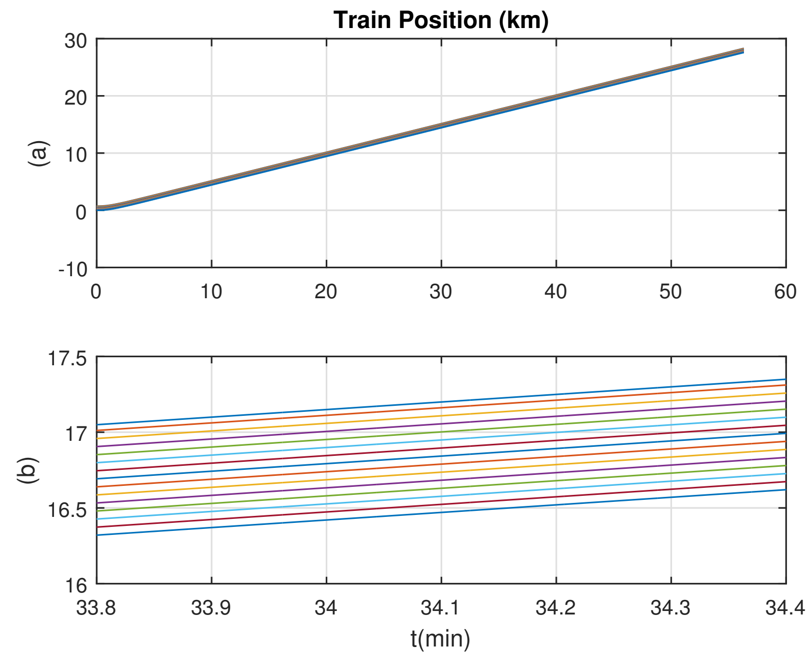

Figure 4.14 – Simulation results of a 15 cars train on the real terrain. The train cars position time history. A simple proportional speed controller with feedback linearization is applied only for the lead locomotive.

Figure 4.15 illustrates that the corresponding control effort, applied only on the lead locomotive, increases to compensate the terrain gradient.

Then, the same experiment was performed considering a remote locomotive in the place of the last wagon. In that case, the lead locomotive is followed by 13 wagons and then by a remote locomotive. In that case, the train mass is $M = \begin{bmatrix} m_l & m_w & m_w & \dots & m_w & m_l \end{bmatrix}^T$. The train total length $L = 766$ m corresponds to the 15 coupled cars. The remote locomotive center of mass is assumed to be in the zero simulation track distance at $t = 0$ s, so that the lead locomotive center of mass is around the position 728 km at $t = 0$ s.

Lead and remote consists were considered to be synchronously commanded, i.e: the remote locomotive follows the lead tractive effort. In Figure 4.16, one can notice that the lead locomotive effort magnitude is reduced as expected due to the distributed power scheme: the remote locomotive helps the lead one the task of moving the train forward.

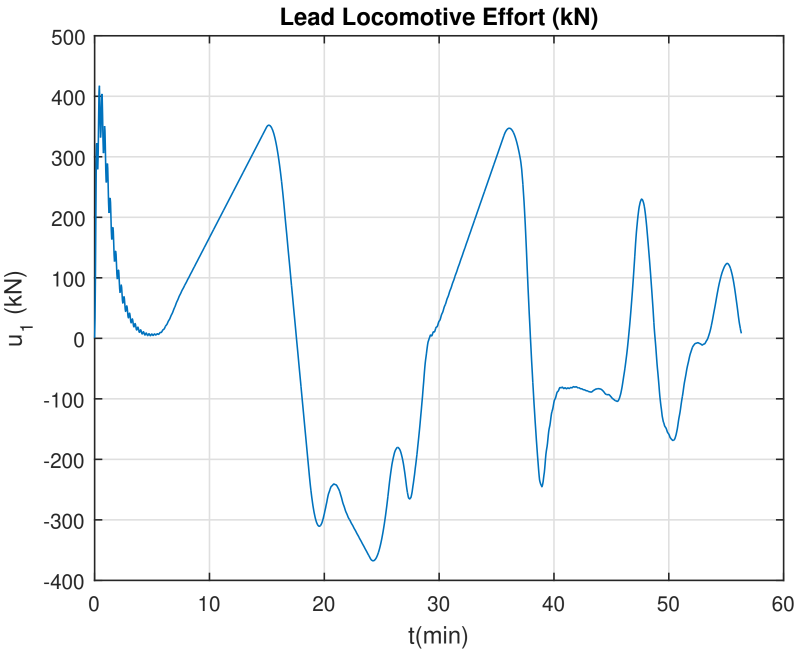

Figure 4.15 – Simulation results of a 15 cars train on the real terrain. The lead locomotive control effort. A simple proportional speed controller with feedback linearization is applied on lead locomotive.

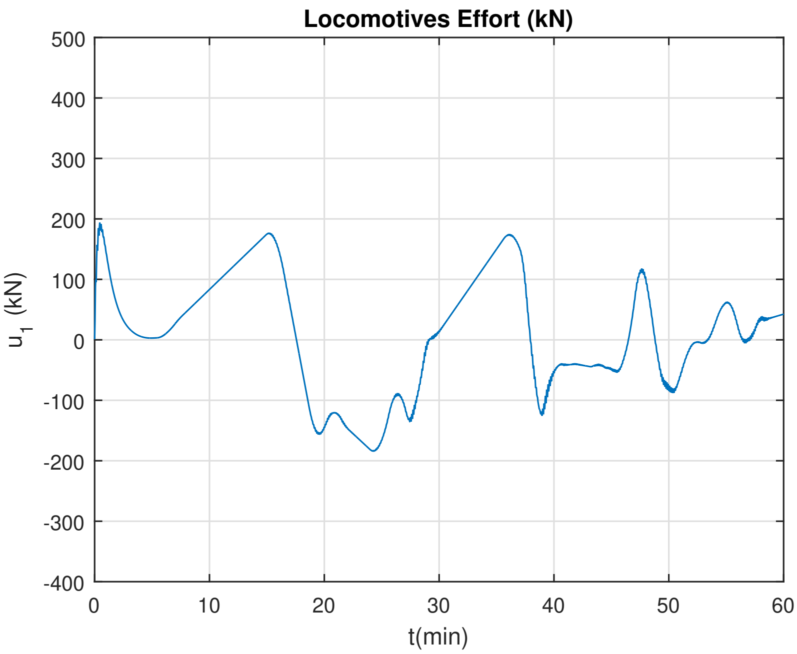

Figure 4.16 – Simulation results of a 15 cars train on the real terrain. The lead locomotive control effort when the remote locomotive is added. A simple proportional speed controller with feedback linearization is applied only on lead locomotive. The same control is applied to the remote one.

Moreover, due to the distributed power, the couplers forces are also attenuated as illustrated in Figure 4.17.

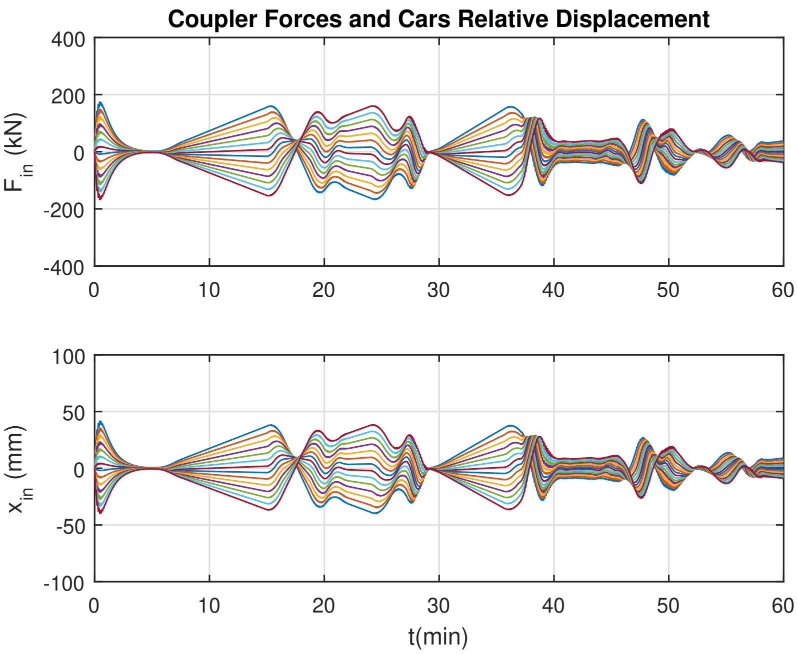

Figure 4.17 – Simulation results of a 15 cars train running on the real terrain. The coupler forces time history when distributed power is considered. A simple proportional speed controller with feedback linearization is applied on the lead locomotive and the same control is applied to the remote one.

In order to illustrate a more real reference speed to be tracked, consider the one in Figure 4.5. This is the original train mean speed from real experimental data as described previously. In the case the train follows an optimal planned speed, that mean speed is also the reference speed. In this case, we assume that the planned speed accounts for the travel time and fuel consumption minimization for the 2-0-0 train described in Section 2.3.

The 71 cars train mean speed will be applied here, though, as a reference speed for our example of a 15 cars train just to verify the controller ability to track a more real reference speed. In this case, one can also verify from Figure 4.18 that the lead locomotive indeed tracks it and the whole train follows it. The corresponding couplers displacement are also illustrated in Figure 4.19.

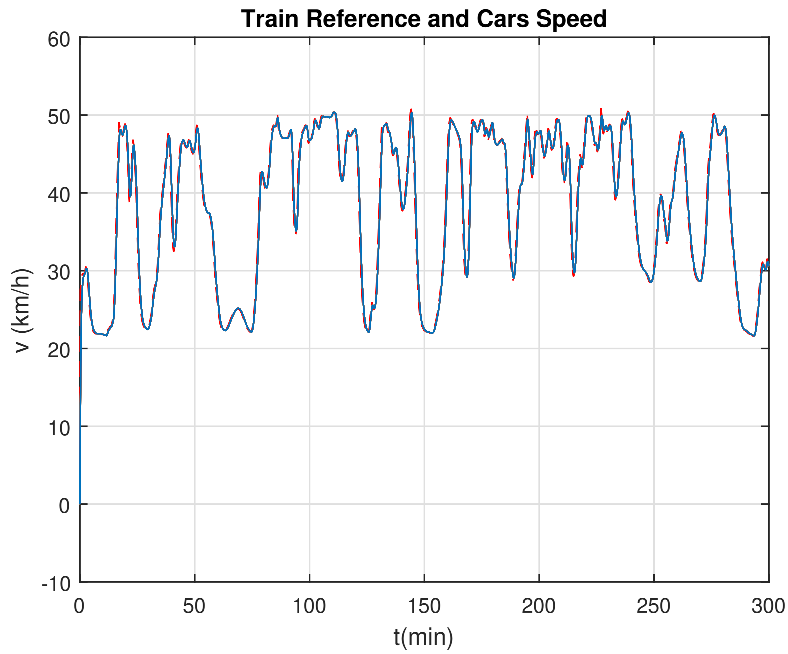

Figure 4.18 – Simulation results of the 15 cars train simulated on the real terrain and a time varying reference speed. The train cars speed time history. A simple proportional speed controller with feedback linearization determines the lead locomotive control action, also applied for the remote one.

Figure 4.19 – Simulation results of the 15 cars train simulated on the real terrain and a time varying reference speed. The coupler forces time history with the distributed power train. A simple proportional speed controller with feedback linearization determines the lead locomotive control action, also applied for the remote one.

Figure 4.20 illustrates the locomotives tractive effort while the component of the terrain gravity forces on the lead locomotive plan of movement are shown in Figure 4.22.

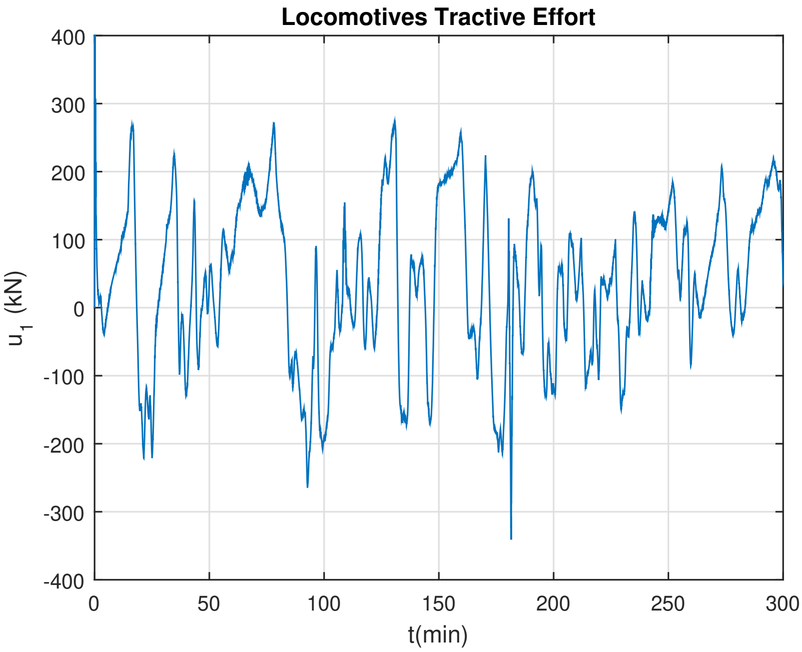

Figure 4.20 – Simulation results of a 15 cars train with the real terrain and a time varying speed reference. The lead locomotive control effort when the remote locomotive is added. A simple proportional speed controller with feedback linearization determines the lead locomotive control action, also applied for the remote one.

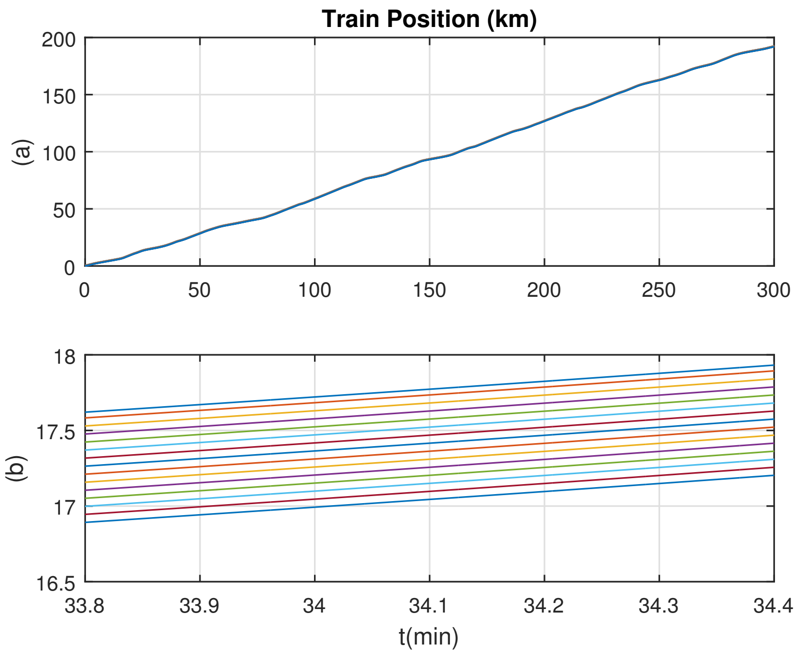

Figure 4.21 – Simulation results of a 15 cars train with the real terrain and a time varying speed reference. The train cars position time history. A simple proportional speed controller with feedback linearization determines the lead locomotive control action, also applied for the remote one.

The train cars position is illustrated in Figure 4.21 and again we observe the train cars following the lead locomotive as expected.

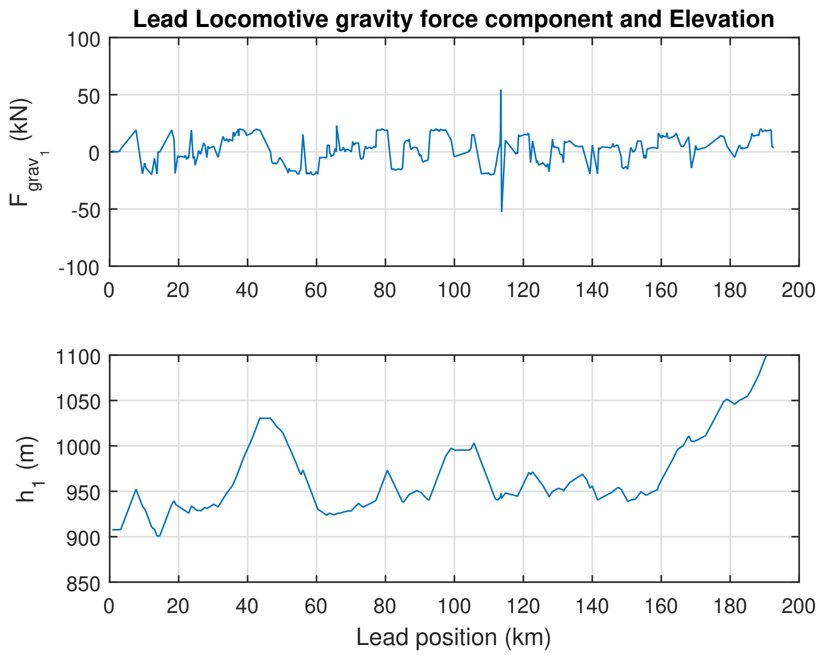

Figure 4.22 – Simulation results of a 15 cars train with the real terrain and a time varying speed reference. The terrain gravity forces acting on the lead locomotive. A simple proportional speed controller with feedback linearization determines the lead locomotive control action, also applied for the remote one.

Now consider a longer train composed by 71 cars, i.e., one lead and another locomotive between 69 wagons. First, by applying to the lead locomotive the proportional speed controller with feedback linearization as before, large couplers forces are observed, in particular around $t = 180$ which corresponds to the kilometer 120 in the simulation, see Figure 4.23 and Figure 4.24.

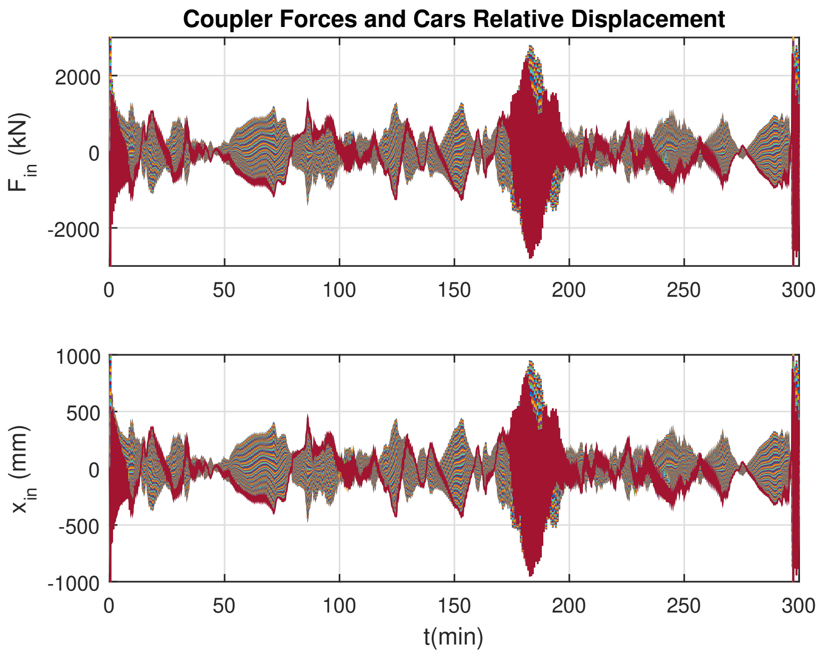

Figure 4.23 – Simulation results for the 71 cars train on the real terrain and a time varying speed reference. The coupler forces time history with the distributed power scheme. A simple proportional speed controller with feedback linearization is used to determine the lead locomotive control and applied on the remote locomotive.

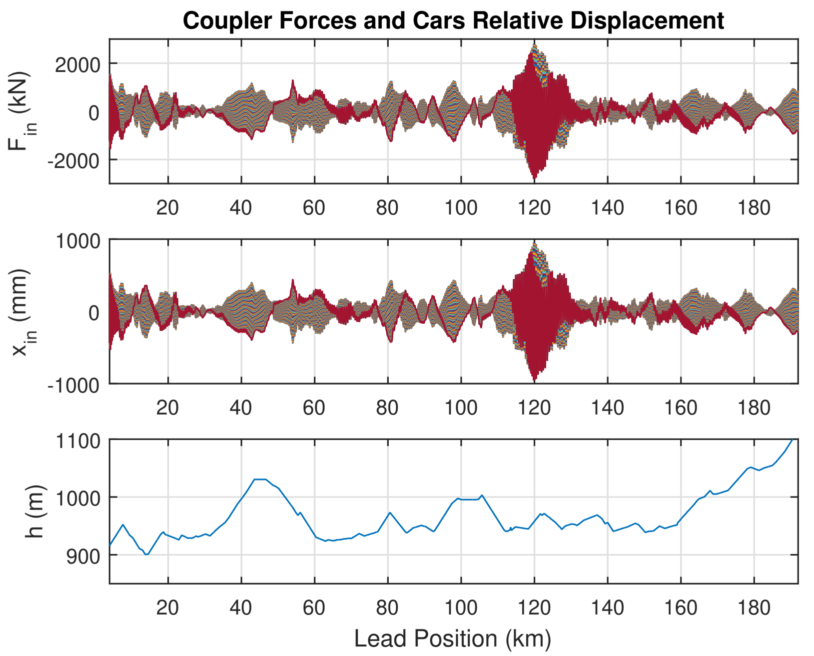

Figure 4.24 – Simulation results for the 71 cars train on the real terrain and a time varying speed reference. The coupler forces time history with the distributed power scheme. A simple proportional speed controller with feedback linearization is used to determine the lead locomotive control and applied on the remote locomotive.

Figure 4.25 illustrates the corresponding control effort synchronously commanded for both lead and remote locomotives. The train position is illustrated in Figure 4.26.

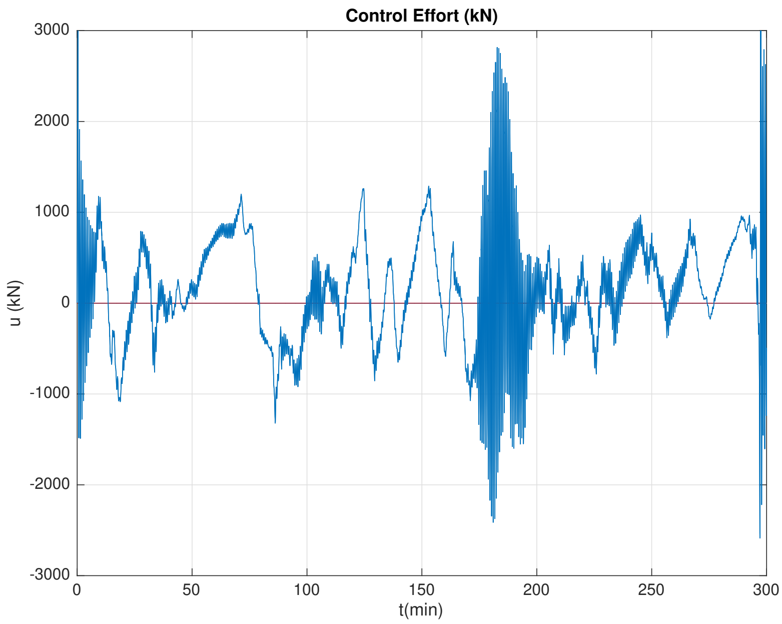

Figure 4.25 – Simulation results for the 71 cars train on the real terrain and a time varying speed reference. The lead locomotive control effort with the distributed power scheme. A simple proportional speed controller with feedback linearization is used to determine the lead locomotive control and applied on the remote locomotive.

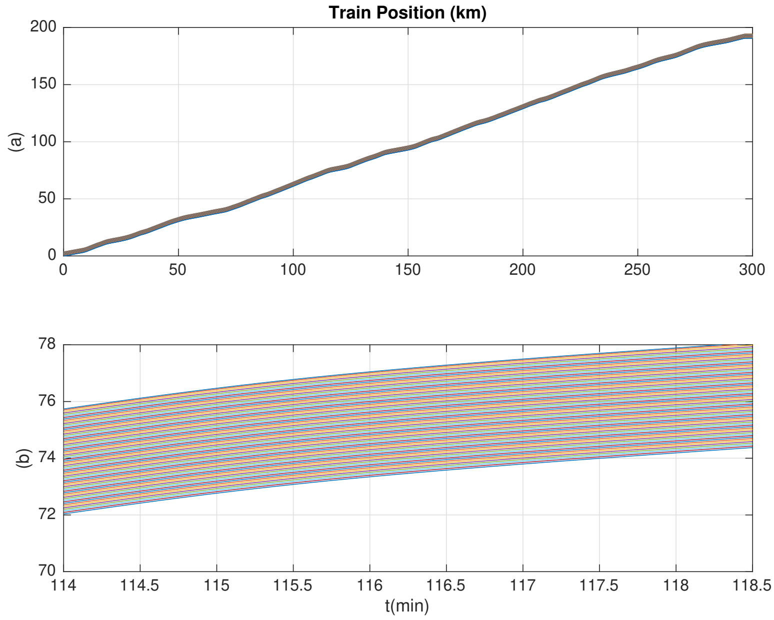

Figure 4.26 – Simulation results for the 71 cars train on the real terrain and a time varying speed reference. The train cars position time history. A simple proportional speed controller with feedback linearization is used to determine the lead locomotive control and applied on the remote one.

One can also verify from Figure 4.27 that the lead locomotive indeed tracks the reference speed and the remaining cars follow it.

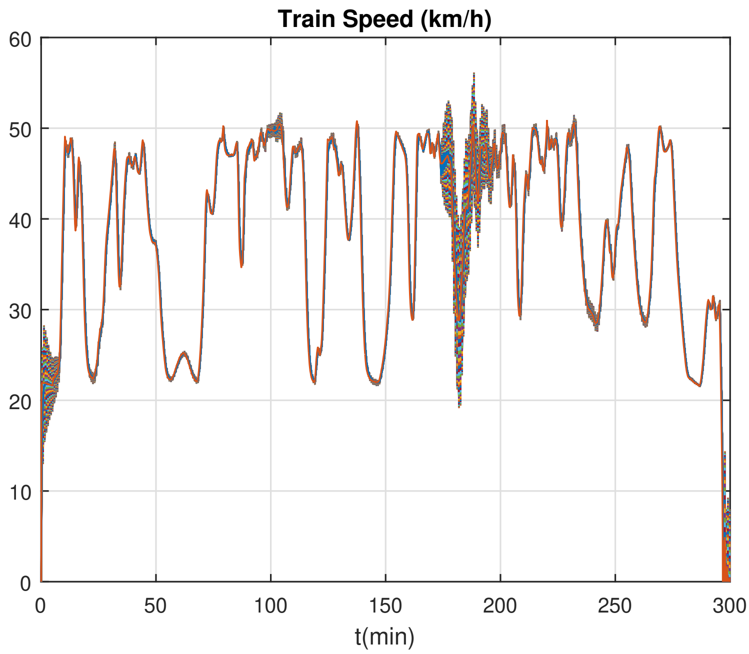

Figure 4.27 – Simulation results for the 71 cars train on the real terrain and a time varying speed reference. The train cars speed time history. A simple proportional speed controller with feedback linearization is used to determine the lead locomotive control and applied on the remote one.

The longer the train, more relative speed and displacement are found. Besides, small relative speed between cars will imply deviations around the plan speed and result in large in-train forces as stated before. In general, car air brakes are also active is some descending slopes to help locomotives dynamic braking in avoiding stretched couplers. In this case, very large coupler forces are encountered because this reference speed plan was calculated considering also the air brakes application although we did not included it in this first controller.

Trying to find a combined solution for locomotives efforts and air brakes, the MPC scheme is employed.

4.2 Numerical Simulations with MPC

Regarding the MPC scheme, after the complete cost function weight tuning, the results presented in this section were obtained. The first term penalizes the amplitude of the in-train forces with weight $K_f \in \mathbb{R}$, while the second term penalizes the energy consumption with weigh $K_e \in \mathbb{R}$ via the amplitude of the control signal and the third term penalizes each car deviation from the reference speed with weight $K_v \in \mathbb{R}$ [63].

The prediction and control horizons were set to $N = N_p = N_c = 3$ and the MPC performance index of interest is implemented with: $K_v = 10$, $K_e = 1 \times 10^{-15}$ and $K_f = 2.4 \times 10^{-12}$. The decision variable initial guess is set to zero in every MPC window $U(0) = \begin{bmatrix} 0 & \dots & 0 \end{bmatrix}^T$.

Lead and remote locomotives tractive efforts upper bounds were set to 659.3 (kN) while its lower bounds were 377.2 (kN). Those are real values, maximum and minimum efforts extracted from data on the Figures 2.4 and 2.5 although no difference in the bounds is set depending on the train speed, notches are also not considered.

With the MPC approach first for the 15 cars train, couplers forces are reduced as shown in Figure 4.28 in comparison to Figure 4.19. In this case, the MPC generates the control effort for the lead and remote locomotives and for the wagons brakes. It is clear that the control signal in Figure 4.29 remains on a limited region having a suitable profile to track speed reference changes while reducing couplers forces. Air braking is exploited when descending hills.

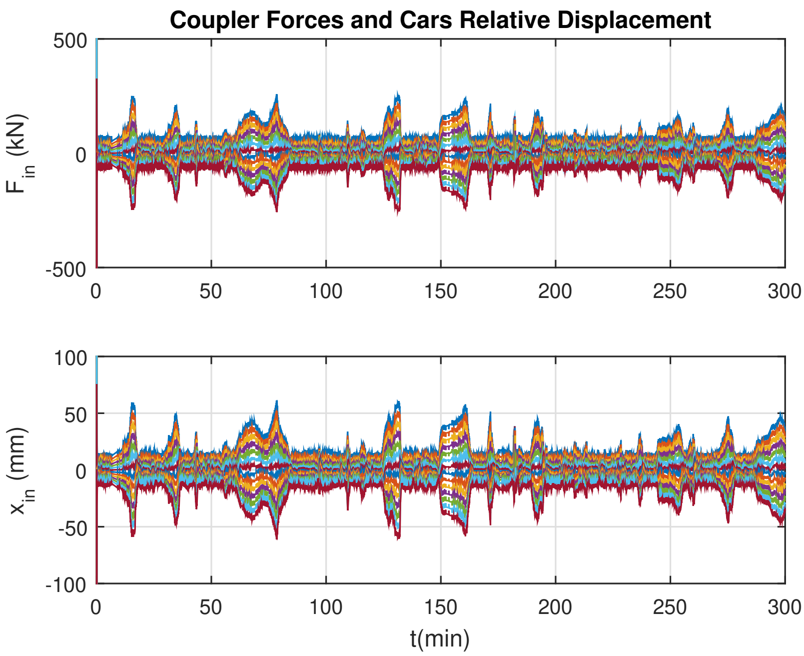

Figure 4.28 – Simulation results of a 15 cars train with the real terrain and a time varying speed reference. The couplers force time history. The speed reference is tracked. Distributed power and air braking are exploited.

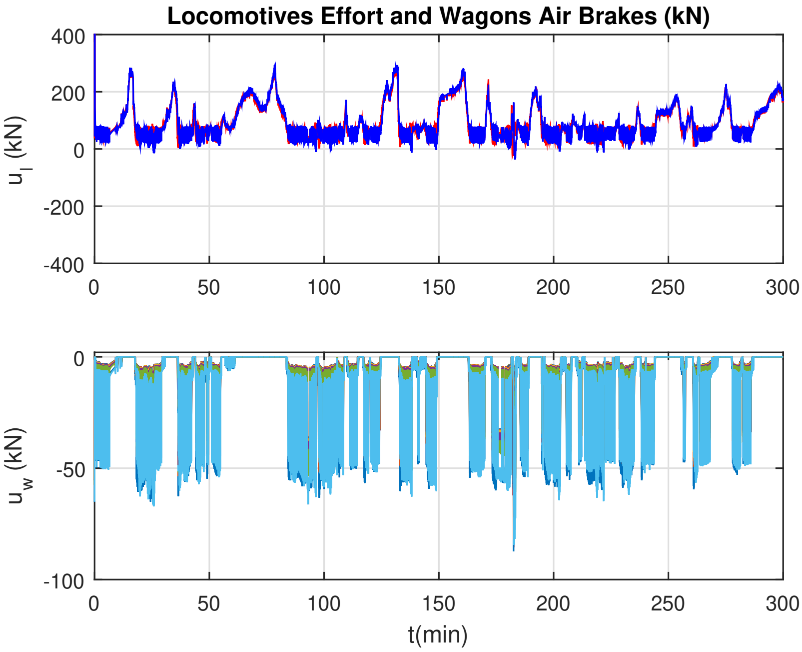

Figure 4.29 – Simulation results of a 15 cars train with the real terrain, a time varying speed reference and the MPC approach. The lead/remote locomotives control effort and the wagons brakes.

In Figure 4.30, we selected to show the first wagon air brake being applied in descending hills although in Figure 4.29 we can see that in general all air braking wagons are actioned simultaneously, similar to a synchronous application.

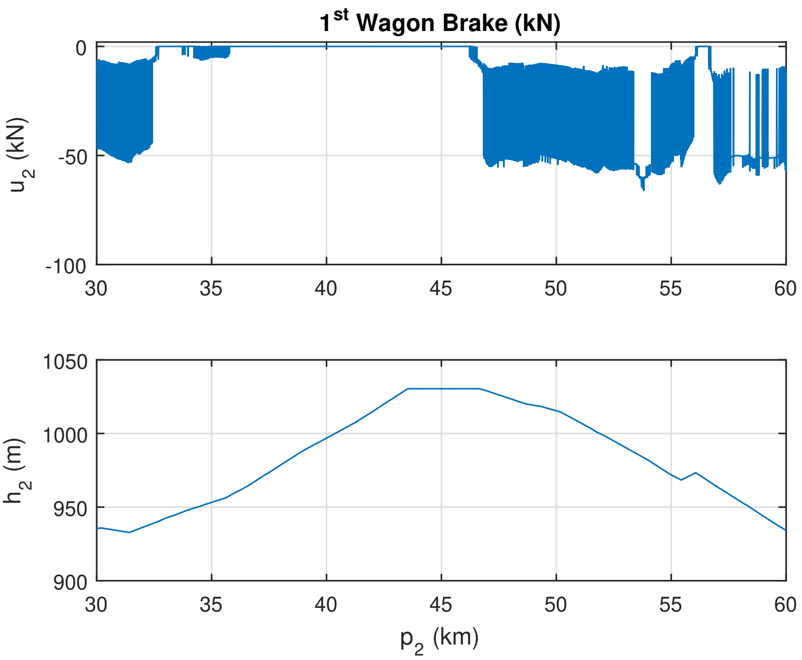

Figure 4.30 – Simulation results of the 15 cars train on the real terrain, a time varying speed reference and the MPC approach. The first wagon brake activation.

Once again, speed tracking can be seen in Figure 4.31 and cars position in Figure 4.32.

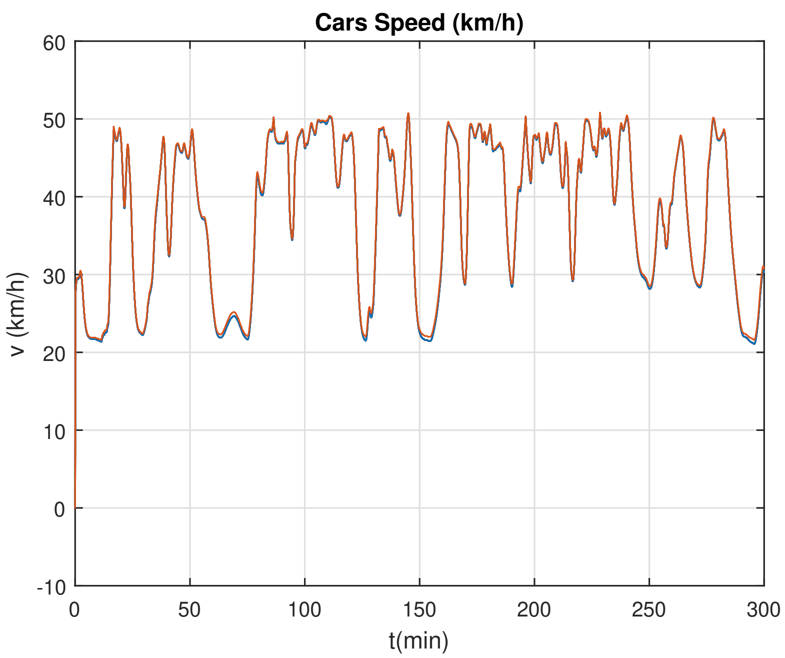

Figure 4.31 – Simulation results of the 15 cars train and the MPC approach. The train speed time history tracking its reference. Distributed power and air braking are exploited.

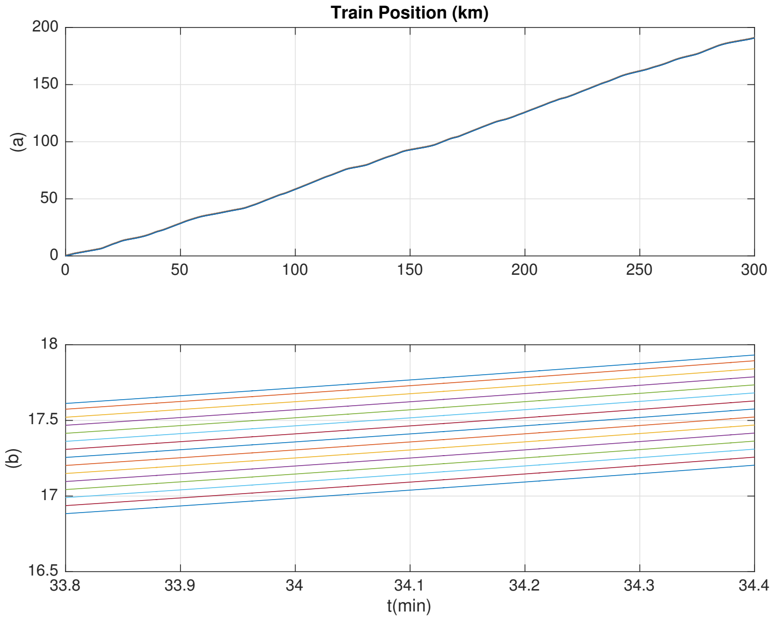

Figure 4.32 – Simulation results of the 15 cars train and the MPC approach. The train cars position time history.

Now, by applying the MPC approach for the 71 cars train with the same weights for the cost function used in the 15 cars case, one can verify that the coupler forces have an improved behavior in comparison to the previous case, see Figure 4.24 and Figure 4.33.

Figure 4.33 – Simulation results of the 71 cars train with the MPC approach and a time varying speed reference. The coupler forces time history. Distributed power and air braking are exploited.

The control signals are presented in Figure 4.34.

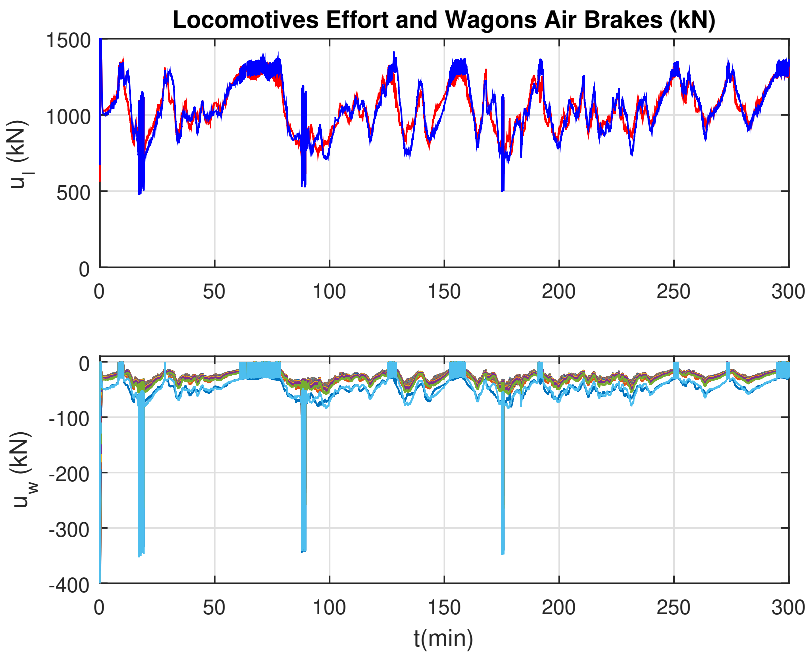

Figure 4.34 – Simulation results of the 71 cars train on the real terrain, time varying plan speed and the MPC approach. The lead/remote locomotives control effort and the wagons brakes.

Figure 4.35 and Figure 4.36 shows again the expected speed tracking of the train.

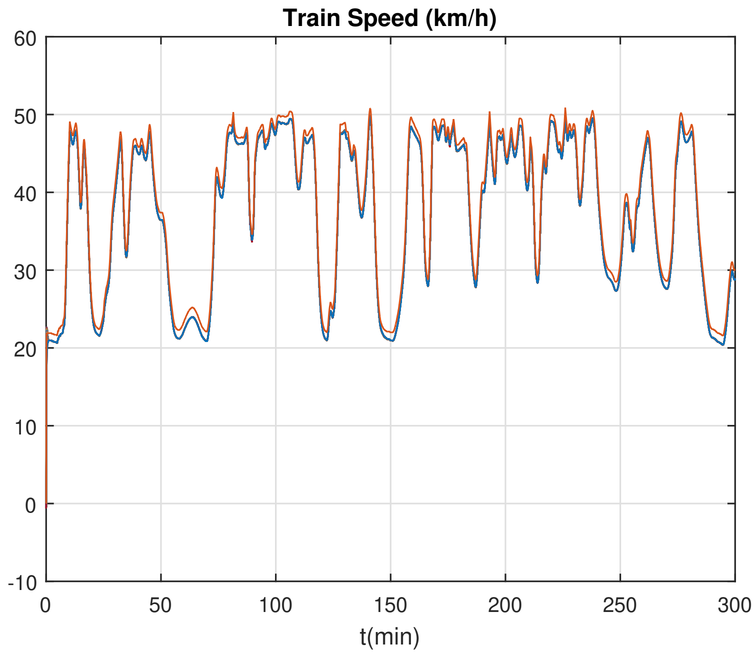

Figure 4.35 – Simulation results of the 71 cars train on the real terrain, time varying plan speed and the MPC approach. The train speed time history. Distributed power and air braking are exploited.

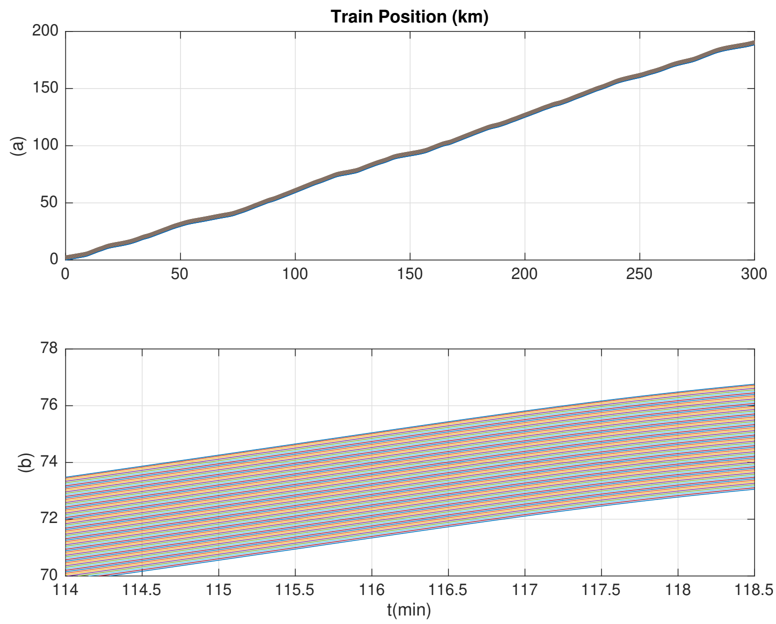

Figure 4.36 – Simulation results with 71 cars and MPC approach. The train cars position time history.

In order to further reduce the in-train forces, the corresponding weight K_f in the cost function is increased four times. In Figure 4.37 we see the expected result after the tuning change at the price of more chattering braking efforts, according to Figure 4.38 as the control reacts to the chosen cost function weights.

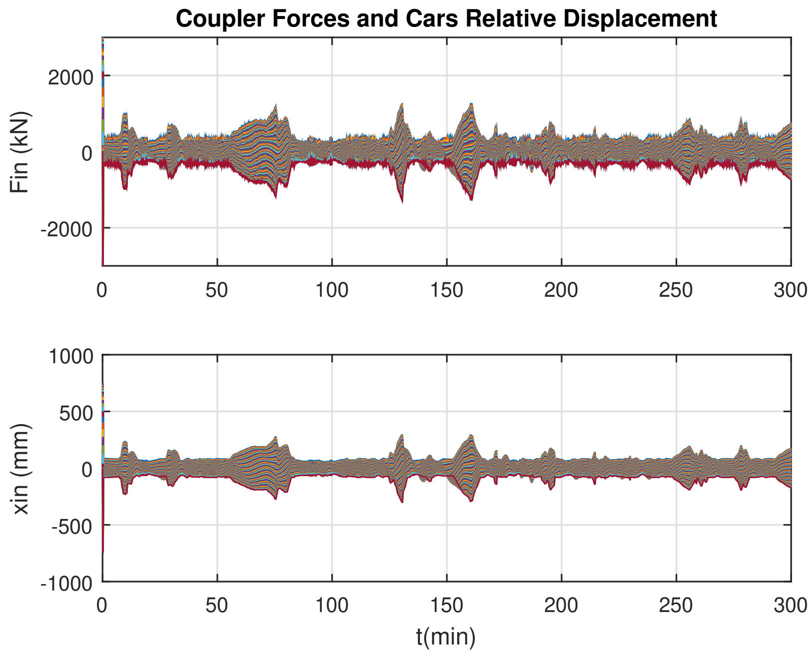

Figure 4.37 – Simulation results of the 71 cars train on the real terrain, time varying reference speed and the MPC approach. The coupler forces time history with $K_f = 9.6 \times 10^{-12}$. Distributed power and air braking are exploited.

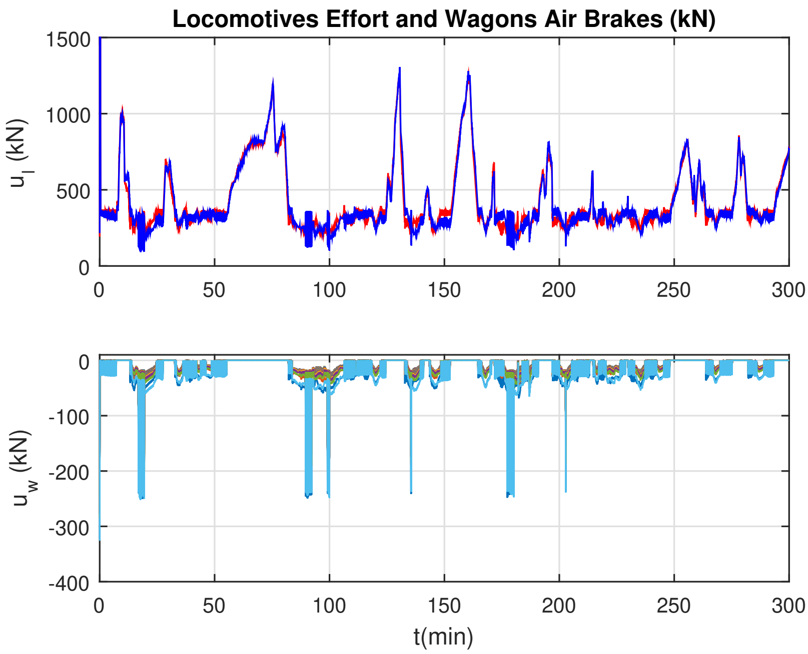

Figure 4.38 – Simulation results of the 71 cars train on the real terrain, time varying reference speed and the MPC approach. The lead/remote locomotives control effort and the wagons brakes with $K_f = 9.6 \times 10^{-12}$.

However, the plan speed tracking error increases as expected, see Figure 4.39. The final tuning should then accommodate the desired train handling performance, with the allowed deviation from the planned speed and fuel consumption expectations.

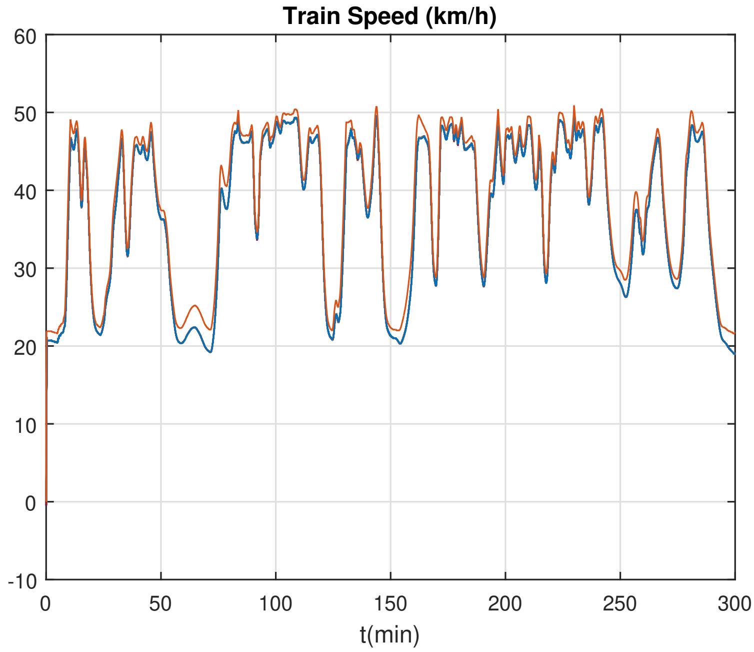

Figure 4.39 – Simulation results with 71 cars, time varying reference speed and the MPC approach is applied with $K_f = 9.6 \times 10^{-12}$. The train cars speed time history. Distributed power and air braking are exploited.

Chapter 5

Conclusions and Future Work

This dissertation proposed an automatic driving procedure for Heavy Haul Trains via the Model Predictive Control methodology. First, a modeling and simulation scheme is applied to real freight trains operations. Then, the objective of evaluating the applicability of a moving horizon strategy optimizing the tradeoff among couplers forces, travel time and fuel consumption is successfully achieved. A train dynamics short term prediction is performed, especially to investigate the train handling consequences of the terrain forces effect combined with train tractive and braking efforts trying to avoid breaking couplers and train derailments that increase operational costs.

The numerical simulations in this work apply the described nonlinear and linearized model to the "Ferrovia do Aço" with a real train configuration. The important benefit of Distributed Power (DP) for train handling in freight trains operations is ratified once again with the adopted speed tracking controller.

Besides, Chapter 4 demonstrates how the terrain forces are a relevant factor in the study of train dynamics even if only modest slopes are present as the train mass is in the order of thousands tons. Also, train length is significant, which makes different cars to be placed in various gradients simultaneously, producing relative displacement and speed between them. Small deviations in cars relative displacement and speed can have a significant impact on train handling due to the high order of couplers parameters.

The obtained results allow us to conclude that the model predictive control is a promising strategy to solve the trade off associated with heavy haul trains operation. It can successfully treat the train handling problem by choosing appropriate weights in the objective function. Since a previously plan speed from real operation is tracked in the proposed performance index, a reference speed can also take into account the travel time schedule and fuel consumption, while treating train handling issues.

Generally speaking, the model predictive controller logic brakes the train when it is mainly descending a hill to avoid the natural effect of stretched couplers. In contrast, for ascending slopes, tractive efforts on the locomotives are needed to assure speed tracking.

Model predictive control can be applied independently of the track or train characteristics. Its flexibility of choosing an objective function in accordance with the desired performance is an advantage as one can change the cost function and its weights to prioritize what is more important in different situations.

However, the MPC tunning process has revealed to be difficult without a particular methodology for choosing a suitable horizon N and weight gains K_v,K_e,K_f. The computational time implied in the MPC scheme is another drawback of this strategy, especially for real time implementation. In addition, in this simulation environment, the whole state was assumed to be available so that a reliable prediction could be accessible, although in practice a state estimator should be in place.

In terms of robustness with respect to uncertain parameters, a few tests with variations in the train mass were performed and the presented controller was still able to track the planned speed, suggesting that the model does not have to be necessarily perfectly known. Robust Model Predictive Controllers is discussed in [51].

5.1 Future Work

In terms of modeling the large scale train problem, during the development of this work, it was suggested to investigate the possibly inspiring connection of this problem with the string stability concept [5] and the vibration model of mechanical systems [49], [45].

In this dissertation, the tractive effort was considered to be the decision variable for the optimization loop. In practice, though, the power level (throttle) would be chosen and, depending on the train speed, it would be converted into the effective tractive effort or dynamic braking applied to the locomotives. Thus, the locomotives notches should be included in the analysis respecting Figures 2.4 and 2.5 as not every possible optimal tractive effort can be applied in reality.

Furthermore, it was assumed that the reference speed v_r and the δ term in (2.7) were constants inside each horizon in the linear MPC adopted. This assumption might be reasonable in the case of short horizons. Nevertheless, with more real constraints to be considered, such as rate limits of change, train handling desired real performance might require longer horizons to be achieved. As the time horizon increases, the considered objective function in the presented form would no longer include correctly the terrain forces prediction, which is truly relevant in the analyses as already shown.

Also, Model Predictive Control ability to find the optimal sequence of commands already taking into account the involved constraints is a powerful characteristic to be explored with real operation restrictions such as the track maximum speed, notches rate limits, etc. In this work, real world constraints were relaxed and, for example, air braking efforts models were not explored. Also, fuel consumption models should be used in order to properly evaluate the tradeoff in rail operations, core of this study. Then, with the addition of more real constraints, it would be interesting to proceed the investigation of the advantages of a constrained MPC in comparison to the unconstrained but saturated implementation.

In addition, there is still room for research in computationally efficient ways of implementing the proposed control in real time. A linearized model was implemented in the expectation that it could reduce the algorithm calculation time but a natural extension of this work is to treat the problem as a nonlinear model predictive control, substituting the coupler simplified model for its nonlinear version. For this, the continuous time optimal control problem can be solved in different manners.

Just to mention a few, some continuous time optimal problems can be optimized indirectly in the continuous time and then discretized for implementation while others direct methods in the literature suggest to perform the discretization first and then optimize, transforming the original infinite optimal control problem into a finite nonlinear programming problem (NLP).

In the latter approach, which resumes the most widespread used techniques for constrained real world optimal control problems, one can choose a sequential methodology with only discretized controls in the decision variable, which is called the direct single shooting method. In contrast, simultaneous ways of solving the problem consider the discretized controls and states in the decision variable such as the direct multiple shooting or collocation methods. More numerical optimal control theory can be found in [16].

Finally, some packages as the ACADO Toolkit and CasADi are indicated for numerical optimization and optimal control problems in general [26], [28], [8], [27],

[22], [55], [54], [43], [42] and [7]. In particular, they can possibly be able to provide computationally efficient solutions to the model predictive control strategy applied to the train large scale problem. Automatic differentiation can help, the sparsity of the optimization problems can be exploited and model reduction strategies can also be tried to help working around the challenges in its efficient implementation.

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