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Fuel efficient control of vehicle platoons using road topography information

Master's thesis in Systems, Control and Mechatronics

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Abstract

Fuel consumption has always been a main concern for the vehicle industry. Freight transports spend much of their income on fuel and transportation of gods can also cause congestion problems in highly trafficked areas. Investments towards development of smarter control methods could possibly lessen these problems. To arrange vehicles in a platoon and with the help of a control algorithm it is possible to travel with a small inter-vehicle spacing. This results in a lowered air drag and better use of road surface. The fuel consumption can also be lowered by knowing the upcoming topography which makes it possible to use the potential energy obtained from hills.

This thesis presents ways to incorporate both the topography information and the platooning behavior in a control strategy that can help reduce the fuel consumption. In this thesis two main control methods are developed for this purpose. One is a greedy approach that optimizes the trajectory for each vehicle without respect to the vehicle behind. The other method plans the trajectory for the entire platoon at once and uses more information to find the most efficient driving pattern. These two control methods are compared to a platoon constructed with gap controllers where the lead vehicle is controlled by a predictive controller.

The result of using a more intelligent control strategy compared to a gap controller proved to save between $2\% - 20\%$ for the greedy approach and $3\% - 24\%$ when more information is used, depending on the specific topography of the road. The optimization routine can also handle different sample lengths and prediction horizon.

Keywords: platoon, optimal, convex, fuel consumption, topography, MPC.

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1
Introduction

Lowered fuel consumption of vehicles is something that has always been in focus for the vehicle industry, and it is becoming even more relevant with rising fuel prices. Efficient driving is something that also companies involved in transportation using heavy duty vehicles (HDV) are interested in. According to the annual report from Volvo Group 2014 [1], 25% – 35% of the expenses for transportation companies relates to fuel. If the fuel usage could be lowered, then the success for freight transports would increase and the environmental strain from emissions would at the same time be lessened.

Two common ways to minimize fuel consumption is to improve the combustion system and increase the utilization of each vehicle. Two other ways are by arranging the vehicles in a platoon and using knowledge of the topography of the road to plan the journey better. Platoon is a name often given to a group of vehicles that drive together on the road in an ordered manor with a short inter-vehicle distance. The result is increased traffic flow and a lower air resistance for each vehicle involved. The air resistance is a major part of the resistive forces that a HDV experience. This is due to their large size and bulky shape. A lowered air resistance would lead to that less energy is required to move the vehicles forward.

Transportation of goods using HDVs will often involve large masses, both from the vehicle itself but also from the load they carry. This makes it harder to maintain a constant velocity going uphill as the engine might not be able to provide sufficient torque. Going downhill can in some cases result in that the vehicle has to break in order to not violate the speed limit. If the topography of the upcoming road section is known with the help of positioning systems, then a smarter driving pattern can be achieved. This is done through the knowledge of the future gains and losses in potential energy.

The gains of driving in a platoon and taking the topography into consideration is already something professional drivers are aware of. Knowledge of eco-driving is even a requirement for getting a driver's licence in Sweden. Even with this knowledge there is a limit to what is possible for a human driver. The driver might not be able to react fast enough if an accident occur when the inter-vehicle distance is small. Driving fuel efficiently also demands focus from the driver to plan the journey in real time with respect to upcoming hills. A control system, that can plan the trip and keep the inter-vehicle distance small, could therefore be of use.

1.1 Background

There have been several projects that uses different techniques to keep a number of vehicles in a close formation, i.e. platooning. Two common variations of platooning is the Adaptive Cruise Control (ACC) and the Cooperative Adaptive Cruise Control (CACC) [2],[3]. These two control methods calculate the control signal with the help of different information about other members in the platoon. The ACC uses only sensor information from the ego vehicle about the nearest neighbor whereas the CACC also receives information from one or several neighbors by vehicle to vehicle (V2V) communication.

The illustration in Figure 1.1 shows a platoon of N vehicles. The ACC and CACC aims to drive the platoon at a common velocity and also keep the inter-vehicle spacing at a reference value. The reference spacing is constant in either space or time. One downside to both of these algorithms is that no topographic information is involved. It could for example be preferable to change the inter-vehicle spacing as preparation for future hills.

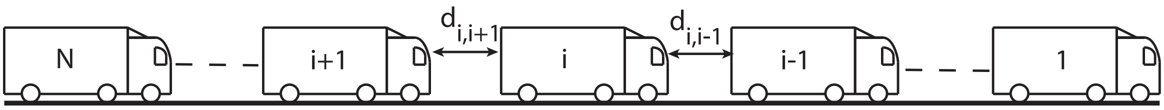

Figure 1.1: A platoon of vehicles N vehicles.

There exists ways to involve the topographic information from Global Positioning Systems (GPS) in order to find a more optimal driving pattern. Dynamic programing or Model Predictive Control (MPC) has previously been used for this purpose and has shown possibility to increase driving efficiency [4],[5]. The behavior will be that before a steep hill the vehicle start to accelerate and then slowly decrease its speed during the uphill travel. At the top of the hill the vehicle reaches a low velocity in order to take advantage of the increase in velocity during the downhill section, due to gravity. The result of this method of driving is a lower fuel consumption. Depending on the implementation it is possible for the vehicles to know future velocity changes of other vehicles. This would make the vehicles in the platoon able to follow the predecessor better.

1.2 Aim

Positive result in using knowledge of road topography and arranging vehicles in a platoon has previously been shown but the two strategies are seldom combined. The idea to create a combined controller that includes both strategies could then prove to be efficient. The aim of this project is therefore to analyze the efficiency of a control strategy that combines the two concepts of platooning and topography information in a way that minimizes the energy requirement for the entire platoon.

1.3 Method

A vehicle model will first be developed. Several of these vehicles will then be combined to achieve the model of a platoon. From the model of one vehicle a convex optimization problem will be stated that tries to minimize the fuel with respect to topography and air resistance. This will later be referred to as a Predictive Controller (PC). The optimization routine will then be extended to optimize the path for several vehicles. The optimal path will be found using the Matlab plug-in cvx [6].

The optimization routine will form the basis of two different platooning controllers. The first controller optimizes the path of each vehicle separately. Each vehicle will also be aware of the planed trajectory of its predecessor. This controller will be named Predecessor Knowledge Predictive Controller (PKPC). The second controller optimizes the trajectory for the entire platoon simultaneously. This demands that information is gathered from all other vehicles and more V2V-communication is then a must.

The platoon will be simulated in Matlabs simulation program Simulink, to approximate the behavior. The platoon controllers will be used as MPCs and will therefore optimize the path iteratively at every sample point and the optimal velocity will, with the help of velocity controllers, be applied to each vehicle. In this way the fuel consumption and behavior of the different control algorithms can be compared. A third platooning controller that only optimizes the trajectory of the lead vehicle will be used as a baseline comparison. In this algorithm the following vehicles keep a predefined distance to the predecessor with the help of gap controllers. This method of control will be referred to as Predictive Platooning Controller (PPC)

1.4 Delimitations

The modeling of the vehicle dynamics will not include the choice of gear as this would severely increase the difficulty of the optimization. The number of vehicles in the platoon is also assumed to be constant and outside influences such as traffic lights and other obstacles are not included.

1.5 Thesis outline

In chapter 2 the model of the vehicles are introduced. The first section describes the model that calculates the engine torque from a certain amount of fuel. The second section talks about the forces that acts on the vehicles and how they are expressed. The chapter ends with a display of the different road cases that will be used in this work.

Chapter 3 discusses how the vehicle model can be expressed as a convex optimization problem. The second section in the chapter shows the optimal trajectory for such an optimization.

Chapter 4 discusses how the optimization routine needs to be changed so that all vehicles in a platoon can have its own optimization routine. The second section in the chapter shows the optimal trajectory for such a platoon.

Chapter 5 finds a convex problem that optimizes the fuel consumption for an entire platoon at once, using more information. The second section in the chapter shows the optimal trajectory for such a platoon.

Chapter 6 shows the significant results of the report. These involve the total fuel consumption, heterogeneous platoons, choice of sample length, length of prediction horizon and the effect of modeling uncertainty in the air drag.

Chapter 7 discusses problems and observation that occurred in the work. The end of the chapter will suggest future improvements and extensions.

Chapter 8 makes the final conclusions and analyzes the results.

2
System description

This chapter first describes the model of the engine and the non-linear vehicle model. The parameter values in the model can be found in Appendix A. The different topography cases are introduced at the end of the chapter.

2.1 Engine model

The fuel consumption is the primary concern in this project and an engine model that can calculate the produced torque for a given amount of fuel is then essential. A sample based engine map from fuel to torque was provided as the base of the model. The data was provided by AB Volvo and is from an D13k460 Euro 6 engine.

It was noted that the engine efficiency was highest at around 1200 rpm. The model was therefore constructed to best approximate the engine at that angular velocity. The truck is not expected to vary its speed much from the average velocity and the fuel model therefore only needs to approximate certain rotational velocities. The approximation of the engine was done using a first order polynomial fit. In Figure 2.1 the relevant angular velocities are shown in comparison to the model. The range is approximately between 60 and 90 km/h.

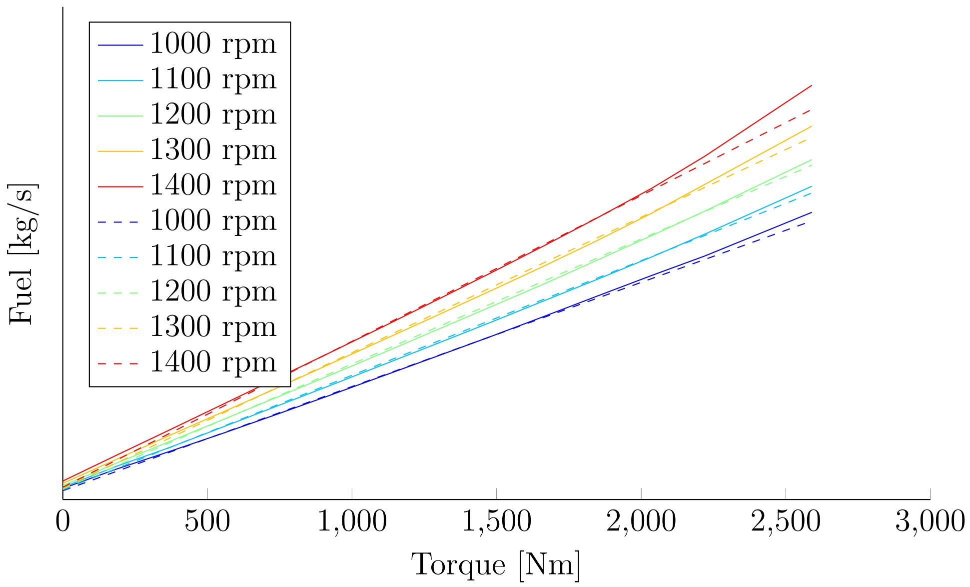

Figure 2.1: The model of the engine in dashed lines and the actual engine data.

2.2 Truck model

The vehicle model will be used both in simulation and in optimization algorithms to find the optimal driving pattern. A simple model is therefore wanted in order to decrease the overall computation time. The model consists of the powertrain and external forces and both are explained here briefly. Inspiration was taken from a similar model that was used in [7].

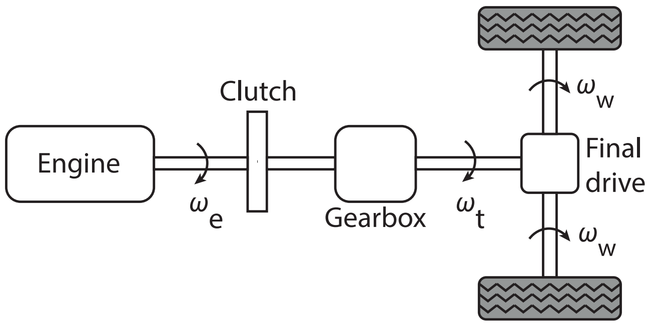

Figure 2.2: Illustration of the powertrain of the vehicle.

The powertrain can be seen as the combination of an engine, clutch, gearbox and a final drive, see Figure 2.2. The clutch is not considered in this model and all shafts that transport the torque are assumed to have no dynamics.

The model for the torque generated by the motor is only dependant on the fueling as seen in Eq. (2.1).

$$\delta = c_1 T_e + c_2 \tag{2.1}$$

where δ is the amount of fuel needed to travel one metre. The engine is also assumed to have a rotational inertia J_e. The transmission in the gearbox is modeled as

$$\omega_t = \frac{\omega_e}{i_c} \tag{2.2}$$

$$T_t = i_c n_c T_e \tag{2.3}$$

where n_c is the transmission efficiency and i_c is the gear ratio in the transmission. In this project both coefficients are selected as 1, i.e. the dynamics of the transmission are ignored. The final drive is modeled in the same way by a conversion factor i_f and an efficiency constant n_f according to Eq. (2.4).

$$\begin{aligned} \omega_w &= \frac{\omega_t}{i_f} \\ T_w &= i_f n_f T_t \end{aligned} \tag{2.4}$$

T_w is the output torque from the final drive which is also the torque at the wheels. The angular velocity ω_w is similarly the angular velocity at the wheels if the vehicle is assumed to experience no slip. Again the transmission efficiency is set to 1. This means that the model assumes no losses in the powertrain. The torque seen by the wheels generated by the motor can be calculated to the corresponding force at the wheels as

$$F_w = \frac{1}{r_w} T_w = \frac{i_c i_f n_c n_f}{r_w} T_e \tag{2.5}$$

where r_w is the wheel radius. The acceleration of the vehicle can now be calculated according to Newton's second law as done in Eq. (2.6)

$$m_e \dot{v} = F_w - F_r - F_b \tag{2.6}$$

where m_e is the equivalent mass, F_r is the external resistive forces and F_b is the braking force. The external forces is the composition of the air drag F_{air}, the roll resistance F_{roll} and the gravitational force in slopes F_g as described by Eq. (2.7) and seen in Figure 2.3. The equivalent mass is calculated in Eq. (2.8) and is the mass of the vehicle plus the resistivity that comes from the powertrain's internal inertia.

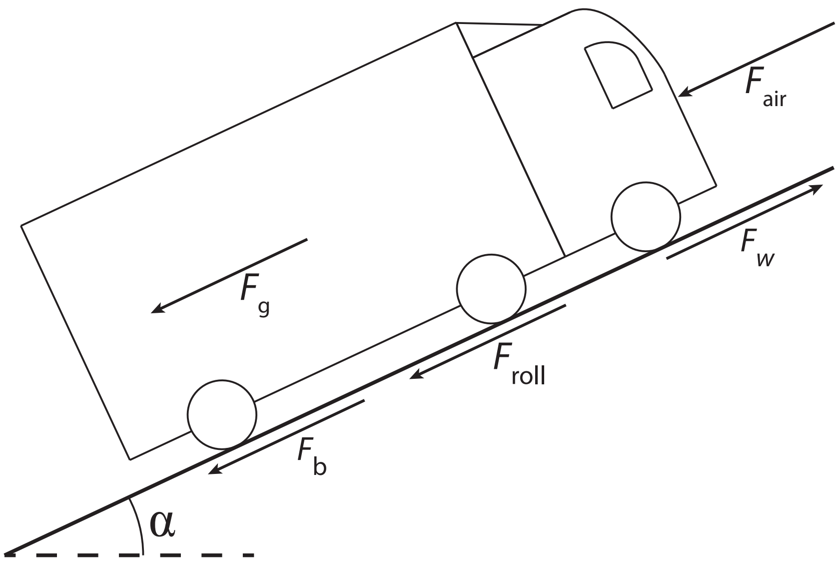

Figure 2.3: The external forces acting on the vehicle.

$$F_r = F_{\text{air}} + F_g + F_{\text{roll}} \tag{2.7}$$

$$m_e = m + \frac{J_w + i_f^2 i_c^2 n_f n_c J_e}{r_w^2} \tag{2.8}$$

In (2.8) J_w is the wheel inertia and m is the mass of the vehicle. The air resistance is calculated as

$$F_{\text{air}}^i = \frac{1}{2} A \rho v^2 C_d \left(1 - \frac{f_i(d_{i,i+1}, d_{i,i-1})}{100}\right) \tag{2.9}$$

where A is the cross section area of the truck, ρ is the air density, C_d is the air drag coefficient and the function f_i describes the reduction in air drag for vehicle i. This reduction is then converted into a percentage reduction, in the air drag formula. This model does not take wind velocity or side-wind into account and the reduction will only depend on the distance to the vehicle behind $d_{i,i+1}$ and the distance to the preceding vehicle $d_{i,i-1}$. The reduction in air resistance is modeled as the composition of three linear functions given as

$$
\begin{aligned}
g_1(d_{i,i+1}) &= K_1 - P_1 d_{i,i+1} = 13 - 0.94 d_{i,i+1}, \quad d_{i,i+1} < \frac{K_1}{P_1} \\
g_2(d_{i,i-1}) &= K_2 - P_2 d_{i,i-1} = 43 - 0.45 d_{i,i-1}, \quad d_{i,i-1} < \frac{K_2}{P_2} \\
g_3(d_{i,i-1}) &= K_3 - P_3 d_{i,i-1} = 52 - 0.47 d_{i,i-1}, \quad d_{i,i-1} < \frac{K_3}{P_3}
\end{aligned}
\tag{2.10}
$$

The first function $g_1(d_{i,i+1})$ describes how the air resistance decreases depending on how close the follower vehicle is. $g_2(d_{i,i-1})$ and $g_3(d_{i,i-1})$ describes how the predecessor affects the air resistance. The coefficients in the functions g are close to the ones used in [7] but with small implementation differences. The air reduction for each vehicle i out of N vehicles can now be calculated as

$$
f_i(d_{i,i+1}, d_{i,i-1}) = \begin{cases} g_1(d_{i,i+1}) & \text{if } i = 1 \\ g_1(d_{i,i+1}) + g_2(d_{i,i-1}) & \text{if } i = 2 \\ g_1(d_{i,i+1}) + g_3(d_{i,i-1}) & \text{if } i > 2 \\ g_3(d_{i,i+1}) & \text{if } i = N \end{cases}
\tag{2.11}
$$

A representation of the air drag reduction is found in Figure 2.4 and shows the reduction for the first three vehicles in a platoon of length four or more. The x-axis shows both the distance to the predecessor and the following vehicle.

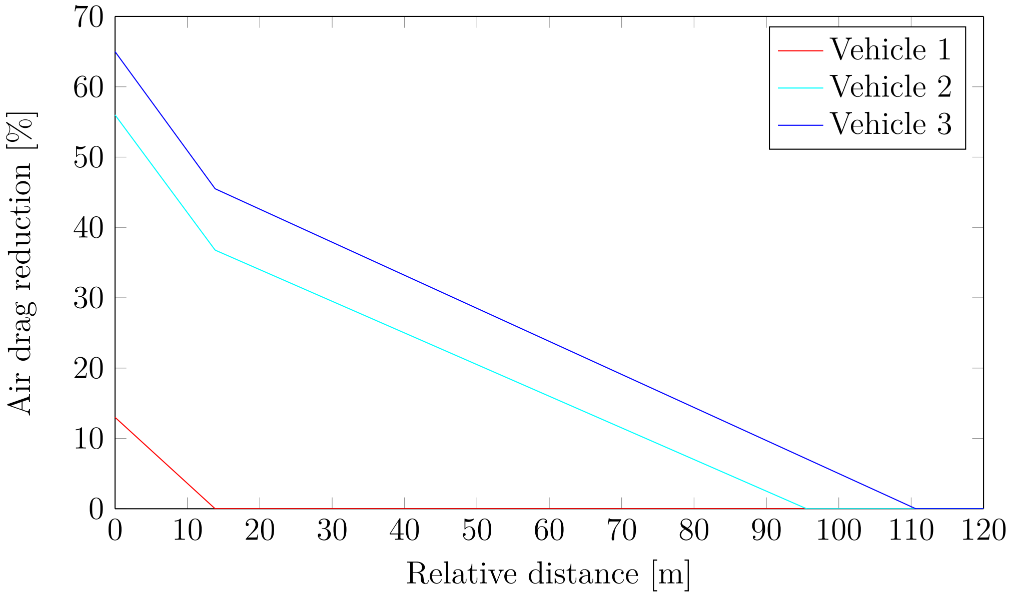

Figure 2.4: The air reduction experienced for the first three vehicles in a longer platoon as a function of distance.

The gravitational force is the longitudinal component of the force induced by gravity and is calculated as

$$F_g = mg\sin(\alpha) \tag{2.12}$$

where α is the slope of the road. The roll resistance is also modeled as a function of the slope and is calculated as

$$F_{\text{roll}} = C_r mg\cos(\alpha) \tag{2.13}$$

where C_r is the roll resistance coefficient.

Now the equation of motion can be described by

$$m_e\dot{v} = F_w - F_{\text{air}} - F_{\text{roll}} - F_g - F_b \tag{2.14}$$

2.3 Hill profile

Three types of constructed road topographies and one based on real measurements will be used in this paper. These road profiles are used to get an understanding of how the optimal velocity profile depends on the road. The road profile therefore needs to be simple but representative. The hill profiles that will be used in this thesis are seen in Figure 2.5. Case 1 and 2 will be used to illustrate how the vehicles prepares for an uphill or downhill section. Case 3 is used to show the effect of longer roads where knowledge of the entire topography is not available. The forth case will be used to analyse the behavior on real road data. Case 4 is the topography data between Borås and Landvetter which has been gathered by AB Volvo. Note that a flat section has been added both at the beginning and at the end of the road.

The angle of the slope is ± 2 degrees in all of the constructed cases. The length of the respective uphill and downhill section is the same for case 1 and 2 and the first two uphill sections in case 3. The downhill section in case 3 is almost twice as long.

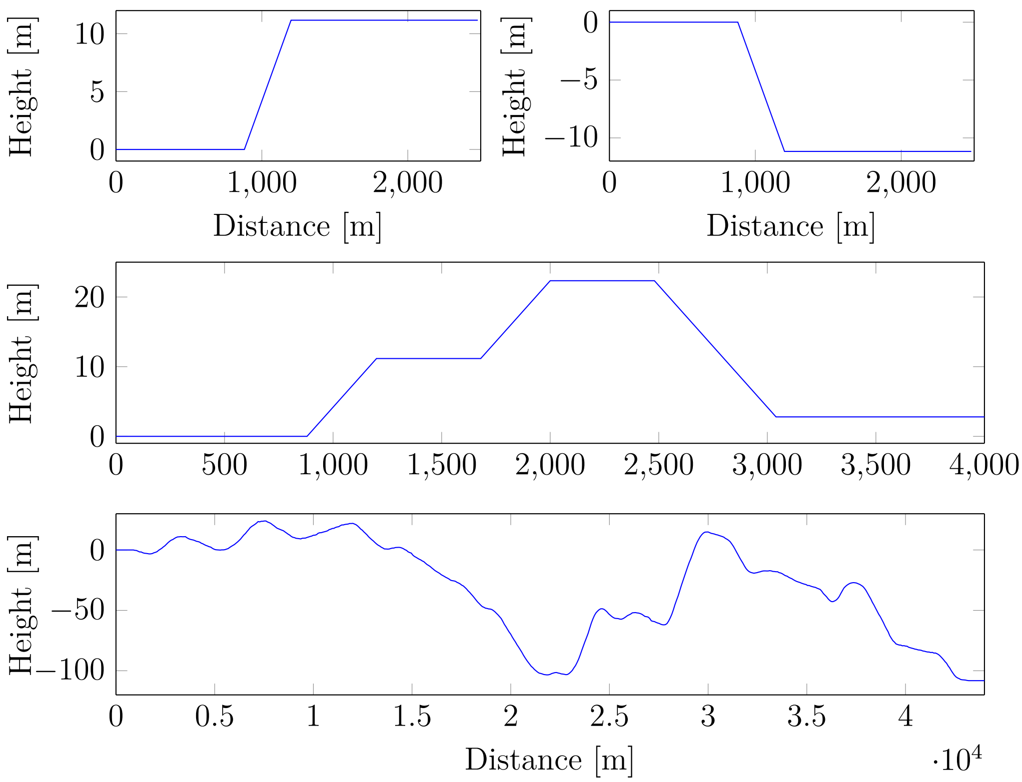

Figure 2.5: The four cases of hill profile that will be evaluated. Top left sub-figure is case 1, top right case 2, the middle is case 3, and the bottom sub-figure is case 4.

3
Predictive controller

This chapter explains how a controller that uses topographic information in order to minimize the fuel consumption for a single vehicle can be constructed as a convex problem, namely the Predictive Controller (PC).

3.1 Convex problem statement

The controller to be designed will later be implemented as an MPC. This means that it finds the optimal trajectory with respect to fuel consumption, over a given prediction horizon at every sample point. The prediction horizon describes how far ahead along the road the optimization problem has knowledge about. The controller uses information about the topography in order to predict the future behavior of the vehicle. A new optimal trajectory is calculated at equally spaced positions along the road. This means that the controller operates in the spatial domain.

The main reason to choose the spatial domain instead of the time domain is that hills are located at certain positions along the road. This makes it impossible to determine the hill location as a function of time unless the velocity curve of the vehicle is known beforehand. If instead the spatial domain is used the hill location can be modeled independently of the vehicle speed.

The computation time required to solve the problem needs to be kept small since the comping unit inside a HDV should be able to solve it. The aim is therefore to describe the system as a convex problem. Convex optimization problems are relatively easy to solve and any local optimum is also guaranteed to be the global optimum [8].

The system dynamics are, as described by chapter 2,

$$m_e \dot{v} = F_w - F_{\text{air}} - F_{\text{roll}} - F_g - F_b \tag{3.1}$$

The kinetic energy for each vehicle is then

$$E = \frac{m_e v^2}{2} \tag{3.2}$$

In Eq. (3.1) the time derivative of the velocity is a function of the square of the velocity, induced by the air drag. If the kinetic energy is used, it is possible to describe the vehicle movement in a linear fashion in terms of kinetic energy, without loosing any dynamics. The derivative with respect to distance of the kinetic energy is the same as the time derivative with respect to time as seen in Eq. (3.3).

$$m_e \frac{dv}{dt} = m_e \frac{ds}{dt}\frac{dv}{ds} = m_e v \frac{dv}{ds} = \frac{d}{ds}E = F_w - F_{\text{air}} - F_{\text{roll}} - F_g - F_b \tag{3.3}$$

The force F_{air} will be described in terms of kinetic energy in the following way.

$$F_{\text{air}} = \frac{1}{2}\rho A C_d v^2 = \rho A C_d \frac{E}{m_e} \tag{3.4}$$

The model in Eq. (3.3) now needs to be discretized in order to be used in the control algorithm. This would result in the discrete model

$$E(k+1) = E(k) + \left(\frac{i_c i_f n_c n_f}{r_w} T_e - \rho A C_d \frac{E}{m_e} - C_r m g \cos(\alpha) - m g \sin(\alpha) - F_b\right) s_d \tag{3.5}$$

where s_d is the sampling distance. The time it would take to traverse each sample distance would then be

$$t_d(k) = \frac{s_d}{v(k)} = \frac{s_d}{\sqrt{2E(k)/m_e}} \tag{3.6}$$

The gravitational force and the roll resistance are functions of the hill angle. These forces can then be seen as vectors of constants since the hill profile is known before hand. This leaves the optimization routine to have the engine torque and the breaking force as optimization variables. All other functions and forces can be calculated from these two variables.

All system properties have now been described and the only thing left is to introduce limitations to the system. The most obvious limitation is that the engine torque has a maximum output power, P_{max}. The engine should also have a minimum torque. This minimum torque should represent the retarding torque produced when no fuel is added to the engine. This is described by the engine model in Eq. (2.1) and states that the engine torque should be greater than $\frac{-c_2}{c_1}$. The vehicle should also stay within the speed limits which puts a constraint on the maximum and minimum velocity, v_{min} and v_{max}. It is also desirable to end with the correct velocity v_{ref}. It is possible to relax this constraint and demand that the final velocity should be greater or equal to the reference velocity. The optimal fuel consumption should still be the same but it could simplify calculations. The final demand is that the vehicle should traverse the prediction horizon within a pre-defined time. This forces the vehicle to maintain the correct average velocity. Note that the various velocity constraints will be stated in terms of kinetic energy.

Another fact is that it might not be possible to fulfill all constraints for certain road sections. It is then possible to add slack variables, i.e. an optimization variable that allows the optimization to violate the constraints. This variable is added to the cost function with a large gain. The result is that the constraints would only be violated if it is necessary in order to solve the problem. The optimization problem for the PC can now be stated as follows.

$$
\begin{aligned}
&\min_{T_e} \quad c_1 T_e + c_2 \\
&\text{subject to} \\
&E(i+1) = E(i) + \left(\frac{i_c i_f n_c n_f}{r_w} T_e - F_{\text{air}} - F_{\text{roll}} - F_g - F_b\right) s_d \\
&E(1) = \frac{m_e v_{\text{init}}^2}{2} \\
&\sum_1^{H_p} t_d \leq \frac{H_p s_d}{v_{\text{ref}}} \\
&\frac{m_e v_{\text{min}}^2}{2} \leq E \leq \frac{m_e v_{\text{max}}^2}{2} \\
&E(H_p) \geq \frac{v_{ref}^2 m_e}{2} \\
&-c_2/c_1 \leq T_e \leq T_{\text{max}}
\end{aligned}
\tag{3.7}
$$

In Eq. (3.7) H_p is the the number of samples that are considered over the prediction horizon. The initial velocity v_{init} is starting velocity of the vehicle. In simulations and implementations on real vehicles, this velocity is the current velocity and should be transmitted to the controller at each sample point. The optimization problem now only consist of convex constraints except for the limit on the engine torque. The torque limit is on the form

$$
T_{\text{max}} = P_{\text{max}} \frac{r_w}{i_c i_f n_c n_f} \sqrt{\frac{m_e}{2E}} = \frac{P_{\text{max}}}{\omega_e} \tag{3.8}
$$

where ω_e is the angular velocity of the engine. To solve this, a linearization of the time with respect to velocity squared will be used. From this time approximation the time can be calculated in a linear way as a function of kinetic energy. The time it takes to traverse each sample point will be approximated with

$$
t_d \approx t_{\text{est}} = a_0 + a_1 \frac{2E}{m_e} \tag{3.9}
$$

where the constants a_0 and a_1 are the solution to the minimization problem

$$
\min_{a_0, a_1} \|t_{\text{true}} - a_0 - a_1 v_{\text{true}}^2\|_\infty \tag{3.10}
$$

where t_{true} is a time vector corresponding to the time it would take to drive one sample distance using a range of representative velocities, i.e. velocities close to the reference velocity. The kinetic energy v_{true}^2 is also calculated from these representative velocities. One important reason that this approximation works is that the vehicles will not wary much from the reference velocity due to being constrained to be within a certain range.

The illustration in Figure 3.1 shows how such a time estimation could be. In this example a vector of 100 points between 72 km/h-78 km/h was generated. The time it would take to traverse an 80 m sample distance was calculated using Eq. (3.6) and the parameters that produced the best fit to this curve was calculated using Eq. (3.10) from the square of the velocity vector.

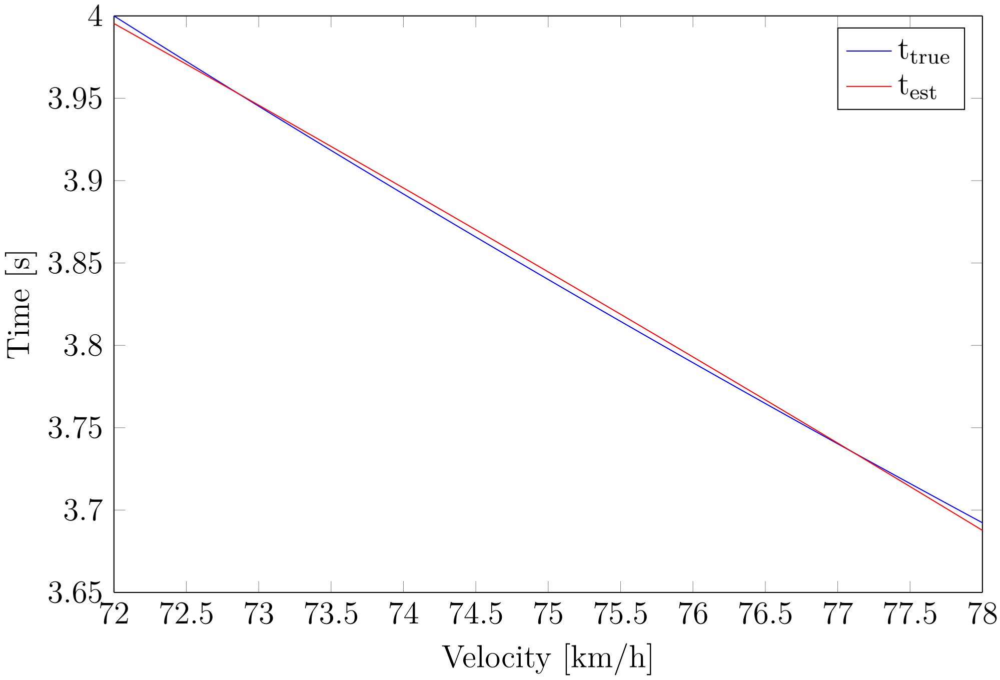

Figure 3.1: The approximation of time compared to the real time to traverse an 80 m distance.

With the new time approximation the constraint on the engine torque can be written as

$$T_e \leq \frac{P_{\max} s_d}{t_{\text{est}}} \frac{r_w}{i_c i_f n_c n_f} \tag{3.11}$$

One final addition needs to be made if the controller is used as an MPC over a long drive cycle. The total travel time and the distance traveled needs to be remembered and added to the time constraint. The expected travel time for the traveled distance must also be calculated. This would give the constraint

$$t_{\text{memory}} + \sum_{1}^{H_p} t_d \leq \frac{d_{\text{memeory}} + H_p s_d}{v_{\text{ref}}} \tag{3.12}$$

where d_{memory} and t_{memory} is the distance traveled and the total travel time up to this point. This constraint needs to be included so that the average velocity for the entire trip is correct instead of over only the prediction horizon.

3.2 Optimal solution for the predictive controller

This section will explain the solution given from the optimization for the first two road cases using a prediction horizon of 2480 m and a sampling distance of 80 m. In the figures it holds in general that when the braking force is not shown, it means that the brake was not used. The dashed black line represents constraints on velocity and torque. The dashed blue lines is marking where a downhill or uphill section starts and the dashed red line is placed where flat ground starts again. The vehicle also has a time constraint that corresponds to keeping an average velocity of at least 75 km/h. The maximum and minimum velocity are in this case set to 70 km/h and 80 km/h.

In Figure 3.2 the result is shown when the first hill case was used, that only has flat and uphill sections. It is visible that the optimization finds it advantageous to increase the vehicle speed slightly before the hill and use full engine power as soon as the hill starts. This is done in order to minimize the velocity change for the road section. This will keep the air resistance to a minimum since it increases with velocity squared and staying close to the average velocity is therefore beneficial.

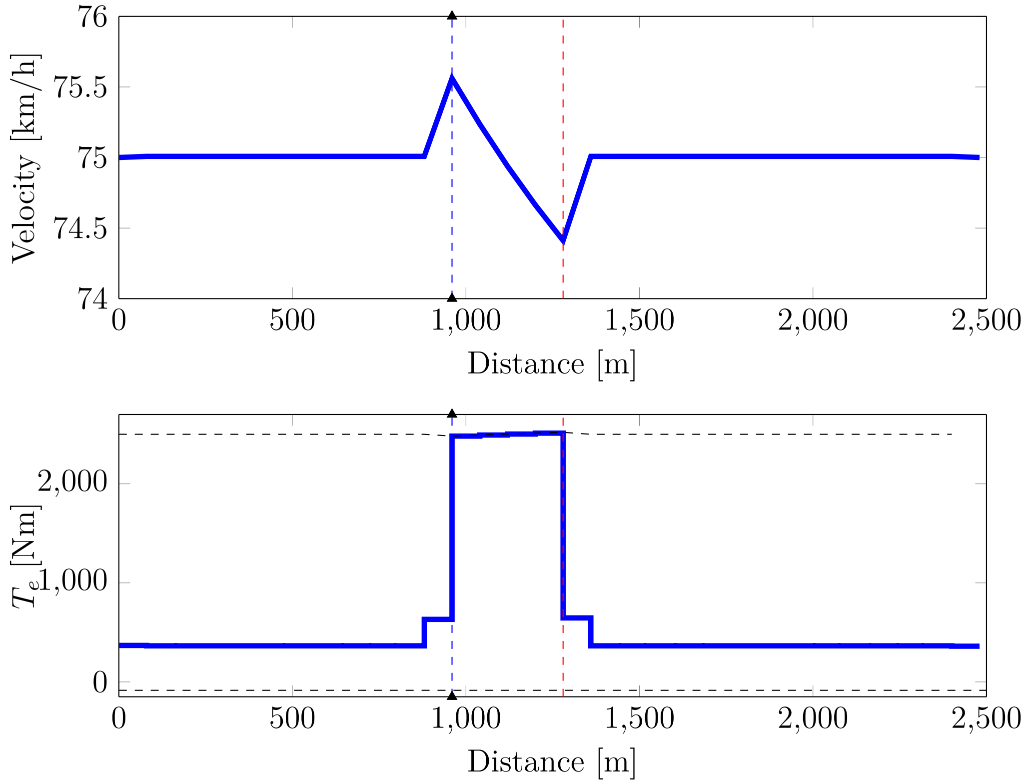

Figure 3.2: Optimal solution with the PC using case 1

Figure 3.3 shows the result for case 2, i.e. a downhill section. Here the vehicle starts to slow down before the drop by setting the torque from the engine to a minimum. At the end of the slope some braking force is required to keep the vehicle within the velocity constraints. Note that after and before the speed changes, the vehicle is traveling with a velocity slightly below than the reference velocity. This is to achieve the correct average speed for the entire road section.

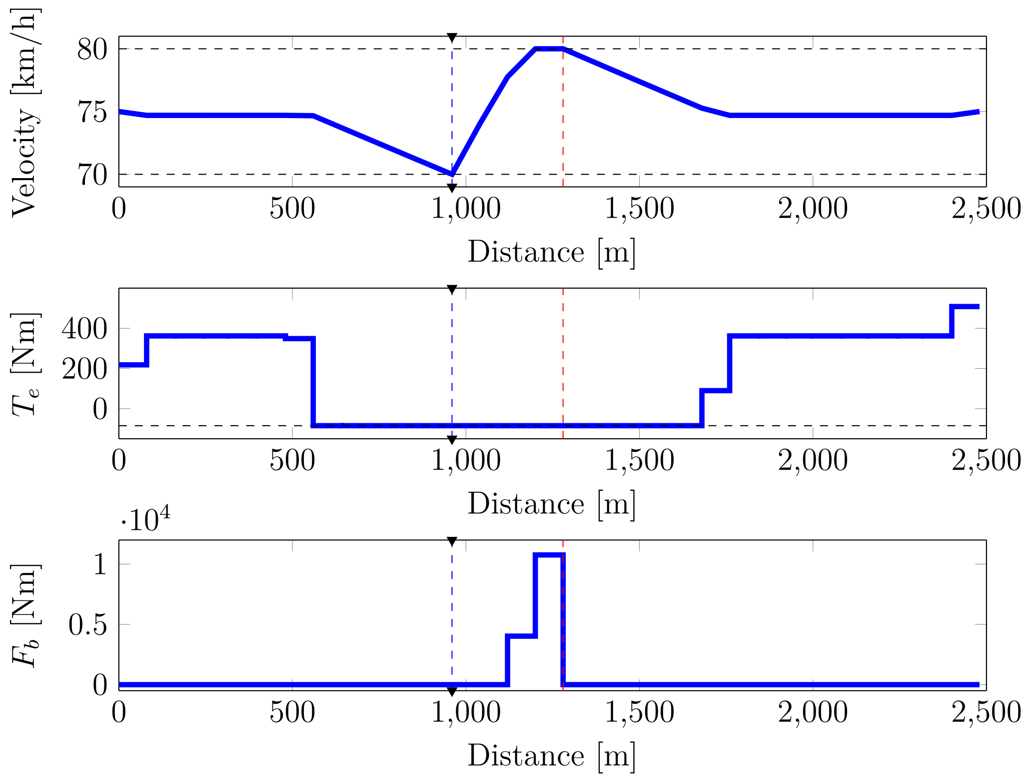

Figure 3.3: Optimal solution with the PC using case 2

4

Predecessor knowledge predictive controller

The predictive platoon controller (PPC) uses one optimization routine along with gap controllers to build up the platoon. This assures that the velocity curve of the platoon takes the topography into account. The extension to this would be to replace the gap controllers with predictive controllers. This gives the possibility for the following vehicles to decide for themselves which velocity they should keep. The only communication between the vehicles is the predicted time t_{est} over the control horizon for the vehicle in front. Each vehicle is also assumed to have a distance sensor so they know how far ahead the preceding vehicle is. In other words, each vehicle optimizes its fueling based on the topography and the predicted velocity profile of the preceding vehicle. This can be seen as a greedy approach as each vehicle tries to drive as fuel efficiently as possible but ignores the effect this could have for the vehicles behind. Such a controller will be named predecessor knowledge predictive controller (PKPC). One assumption that is used in each vehicle is that the vehicle behind is keeping a constant distance of d_{ref} meters. This is to get an approximation of the air drag reduction.

4.1 Convex problem statement

No change is needed compared to the PC case for the first vehicle in the platoon other than that the predicted time to traverse each sample distance needs to be sent to the next vehicle. The rest of the platoon also use the same optimization routine but with slight modifications. The first change is that the vehicles need to be restricted to not drive too close. This is done via requiring a time delay between the vehicles. The constraint states that the time it takes for a vehicle to reach a certain sample distance minus the time it took the previous vehicle to reach the same position, must not be to small. This is done in the constraint stated in Eq. (4.1) where each vehicle also has been given an initial headway time to reach the starting position. This headway time must be approximated when the MPC is implemented in Simulink. A time delay between the vehicles is used so that the distance between them in meters will increase as the velocity increases.

$$t^i(j) - t^{i-1}(j) \geq \frac{d_{\text{ref}}}{v_{\text{ref}}} \tag{4.1}$$

In Eq. (4.1) $t^i(j)$ is the time it takes vehicle i to reach sample point j as done in (4.2).

$$t^i(j) = t^i_{\text{init}} + \sum_{k=1}^{j} t^i_d(k) \tag{4.2}$$

where t^i_{init} is the initial time delay between vehicle i and $i-1$. Unfortunately (4.1) is not a convex constraint. The solution is to use the time approximation previously discussed in Eq. (3.9). The new expression for the time delay between vehicles is then linear in kinetic energy and can be written as

$$t^i(j) - t^{i-1}(j) = t^i_{\text{init}} + \sum_{k=1}^{j} t^i_{\text{est}}(k) - \sum_{k=1}^{j} t^{i-1}_{\text{est}}(k) \geq \frac{d_{\text{ref}}}{v_{\text{ref}}} \tag{4.3}$$

Another term that causes the optimization problem to be non-convex is the air drag. This is because the inter-vehicle distance in meters is not known over the prediction horizon, and the distance is also multiplied with the kinetic energy. The air resistance is therefore linearized around d_{ref} and v_{ref} using a first order Tailor expansion as seen in Eq. (4.4).

$$\begin{aligned} F^i_{air} = \rho A C_d \left(1 - \frac{f_i(d_{\text{ref}}, d_{\text{ref}})}{100}\right) \frac{E_{\text{ref}}}{m_e} + \\ + \rho A C_d \frac{P_{2,3}}{100} \frac{E_{\text{ref}}}{m_e} \left((t^i - t^{i-1}) v_{\text{pred}} - d_{ref}\right) + \\ + \rho A C_d \left(1 - \frac{f_i(d_{\text{ref}}, d_{\text{ref}})}{100}\right) \frac{E - E_{\text{ref}}}{m_e} \end{aligned} \tag{4.4}$$

In Eq. (4.4), v_{pred} is the predicted velocity of the preceding vehicle. The distance to the preceding vehicle is calculated with the approximated time difference multiplied with the velocity of the preceding vehicle. The velocity of the preceding vehicle is calculated using the sent vector of time estimated. The distance to the following vehicle is assumed to be at the reference distance. Also note that the linearization will differ for the last and first vehicle as they will only have a following or preceding vehicle. The constant $P_{2,3}$ is either equal to P_2 or P_3 depending on the position in the platoon.

4.2 Optimal solution for the predecessor knowledge predictive controller

In this section the results from the optimization routine for four vehicles are explained. The black dashed lines are the limiting constraints. The blue and red dashed line correspond to the start and end of a slope respectively where an arrow will indicate the increase or decrease of hill angle.

Figure 4.1 shows the results from the optimization using case 1. Here all the vehicles follow the same velocity curve and this velocity curve looks the same as in the PC case. All vehicles also follow with the closest allowed distance. The first vehicle is drawn in blue and it can be seen that it applies more torque than the rest of the platoon due to the different air resistance. The remaining three vehicles use similar amount of torque and the lines therefore shadow each other in the figure.

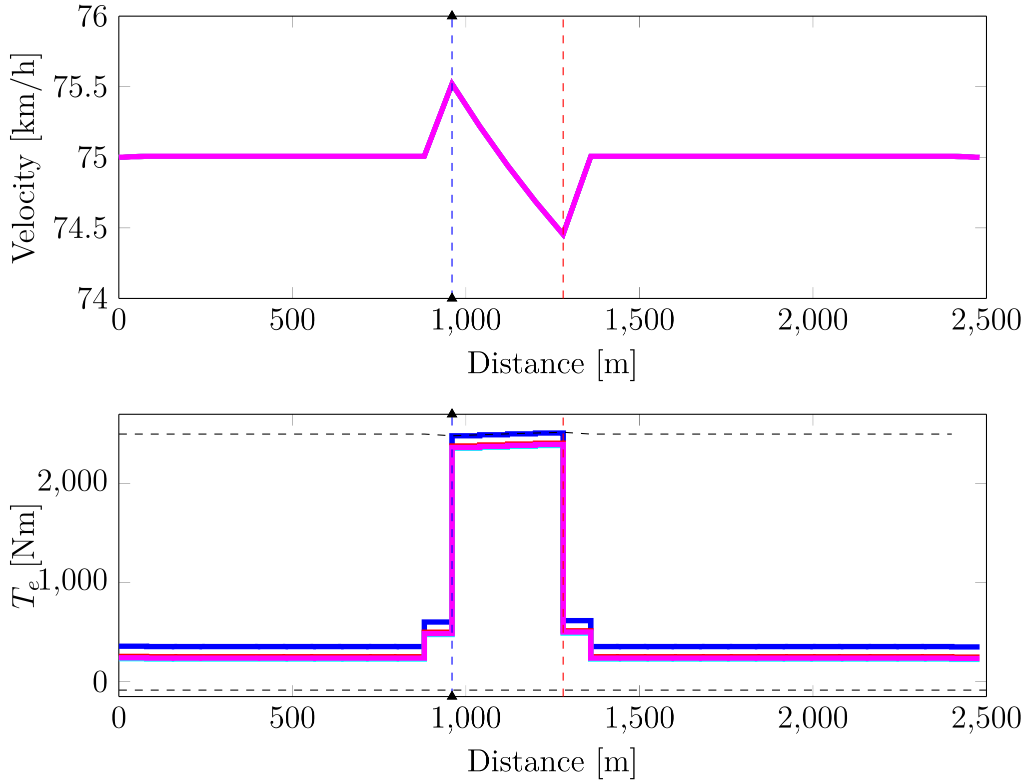

Figure 4.1: Optimal solution with the PKPC using case 1

Figure 4.2 shows the result for case 2 i.e. the downhill road. The color order for the vehicles is blue for the first vehicle, red for the second, cyan the third and magenta is the forth vehicle. The sub figure showing the relative time distance, gap, has the same color order where the gap between vehicle 1 and 2 is in blue, between 2 and 3 is drawn as red and the last gap between vehicle 3 and 4 is cyan.

Well before the downhill starts, the three last vehicles start to separate from the lead vehicle. The reason for this is as follows. The first vehicle finds its optimal velocity trajectory which has the same shape as for the PC. This means that the first vehicle sets the engine torque to the minimum in the downhill section. If the second vehicle drives at close range to the first and also releases the gas in the downhill section, it will soon get to close to the vehicle in front. This is since the air resistance is lower for the second vehicle and the retarding affect is then larger for the vehicle in front. It is also wasteful to use the brake since this would imply that the vehicle could have driven slower at other sections of the road. The solution to avoid to use the brake is then to increase the inter-vehicle distance before the downhill and catch up with the vehicle in front at a later time on the road.

This explained driving behavior is visible in the figure as all vehicles separate and stop the fuel to the engine. By not giving the engine any fuel, it will add a small retarding force. The vehicles start to catch up to each other when the slope has ended. Some small braking force is still required in order to not violate the velocity constraint.

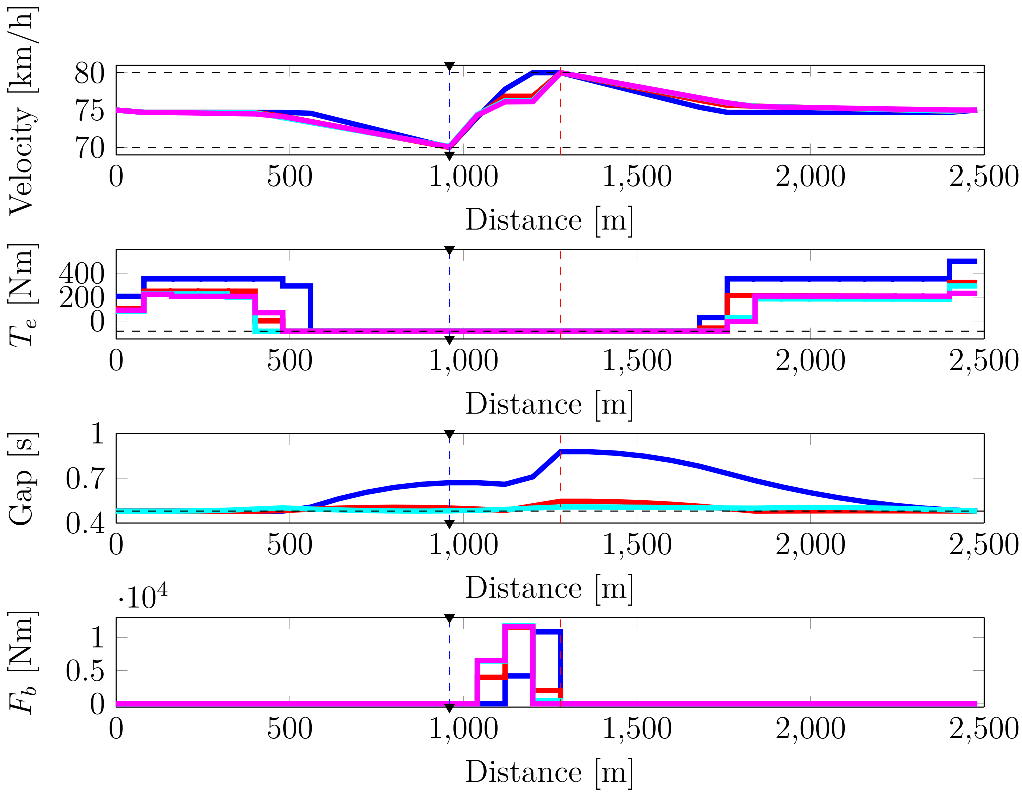

Figure 4.2: Optimal solution with the PKPC using case 2

5

Full knowledge predictive controller

The PKPC can be seen as a greedy approach to control a platoon since all vehicles optimizes its driving pattern with regards only to their own fuel consumption. In order to find a velocity curve that is the optimum in regards to the combined consumption of the platoon, more information has to be shared. This is the purpose of the full knowledge predictive controller (FKPC). It finds the optimal velocity for all vehicles in the platoon and feeds this information to each vehicle. In order to do this, the position and velocity at the current sample position for all vehicles is used.

5.1 Convex problem statement

The resulting problem is similar to the PKPC but calculations for all N vehicles must now be done in the same optimization as seen in (5.1).

$$
\begin{aligned}
&\min_{T_e} \ \sum_{i=1}^{N} \ c_1 T_e^i + c_2 \\
&\text{subject to} \\
&\text{for } i = 1 \text{ to } N \\
&E^i(k+1) = E^i(k) + \left(\frac{i_c i_f n_c n_f}{r_w} T_e^i - F_{air}^i - F_{roll}^i - F_g^i - F_b^i \right) s_d \\
&E^i(1) = \frac{m_e v_{\text{init}}^2}{2} \\
&\sum_{1}^{H_p} t_d^i \leq \frac{H_p s_d}{v_{\text{ref}}} \\
&\frac{m_e v_{\min}^2}{2} \leq E^i \leq \frac{m_e v_{\max}^2}{2} \\
&E^i(H_p) \geq \frac{v_{ref}^2 m_e}{2} \\
&- c_2/c_1 \leq T_e^i \leq T_{\max} \\
&F_b \geq 0 \\
&\text{if } i \text{ is greater than } 1 \\
&t^i - t^{i-1} \geq \frac{d_{\text{ref}}}{v_{\text{ref}}}
\end{aligned}
\tag{5.1}
$$

Note that the air drag needs to be changed slightly in order to be convex. The velocity that is multiplied with the time delay is replaced with the constant v_{ref} and the expression then becomes linear. The new air resistance is described by (5.2). Again the equation needs to be modified for the last and first vehicle.

$$
\begin{aligned}
F^i_{air} = \rho A C_d \left(1 - \frac{f_i(d_{\text{ref}}, d_{\text{ref}})}{100}\right) \frac{E_{\text{ref}}}{m_e} + \\
+\rho A C_d \frac{P_{2,3}}{100} \frac{E_{\text{ref}}}{m_e} \left((t^i - t^{i-1}) v_{\text{ref}} - d_{ref}\right) + \\
+\rho A C_d \frac{P_1}{100} \frac{E_{\text{ref}}}{m_e} \left((t^{i+1} - t^i) v_{\text{ref}} - d_{ref}\right) + \\
+\rho A C_d \left(1 - \frac{f_i(d_{\text{ref}}, d_{\text{ref}})}{100}\right) \frac{E - E_{\text{ref}}}{m_e}
\end{aligned}
\tag{5.2}
$$

5.2 Optimal solution for the full knowledge predictive controller

This section explains optimization results for the FKPC. The blue and red dashed line correspond to the start and end of a slope respectively, where an arrow will indicate the direction. The black dashed lines are the limiting constraints.

Figure 5.1 shows the result obtained by using hill case 1. The difference between the solution from the FKPC and both the PC and PKPC is negligible and the platoon behaves as expected. The inter-vehicle gap stays at its minimum value through out the road section.

Figure 5.2 shows the result from using case 2, the downhill road. The three last vehicles has almost the exact same solution where as the first vehicle, in blue, differs slightly. There is a small increase in the relative distance between vehicle 1 and 2 seen in blue, just before the hill but the gap is much smaller than in the FKPC compared to the the PKPC case. This is because the lead vehicle can adjust its trajectory in order for the following vehicles to drive in a more fuel efficient way. The optimization tries to find the optimum for the entire platoon, not just the optimum for each vehicle as in the PKPC case. This means that it can be advantageous for one vehicle to sacrifice efficiency so that other vehicles can use a better velocity curve. It is the leader who has to adapt most towards the rest of the platoon since the difference in air resistance is greatest between vehicle 1 and 2.

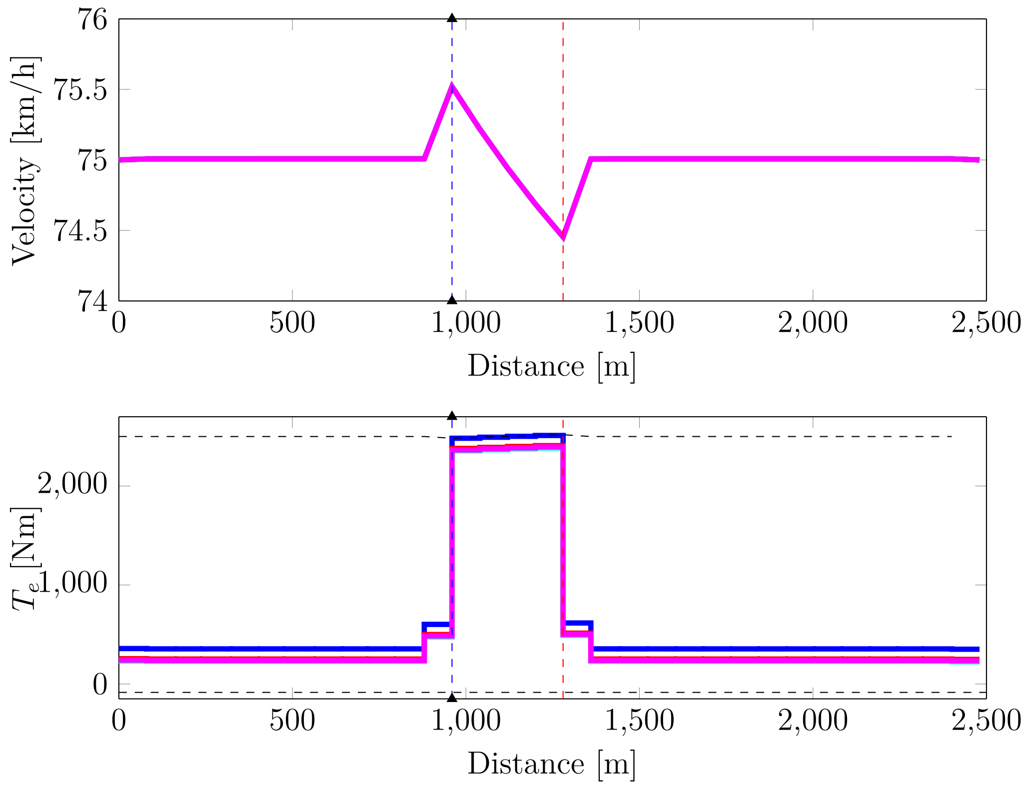

Figure 5.1: Optimal solution with the FKPC using case 1

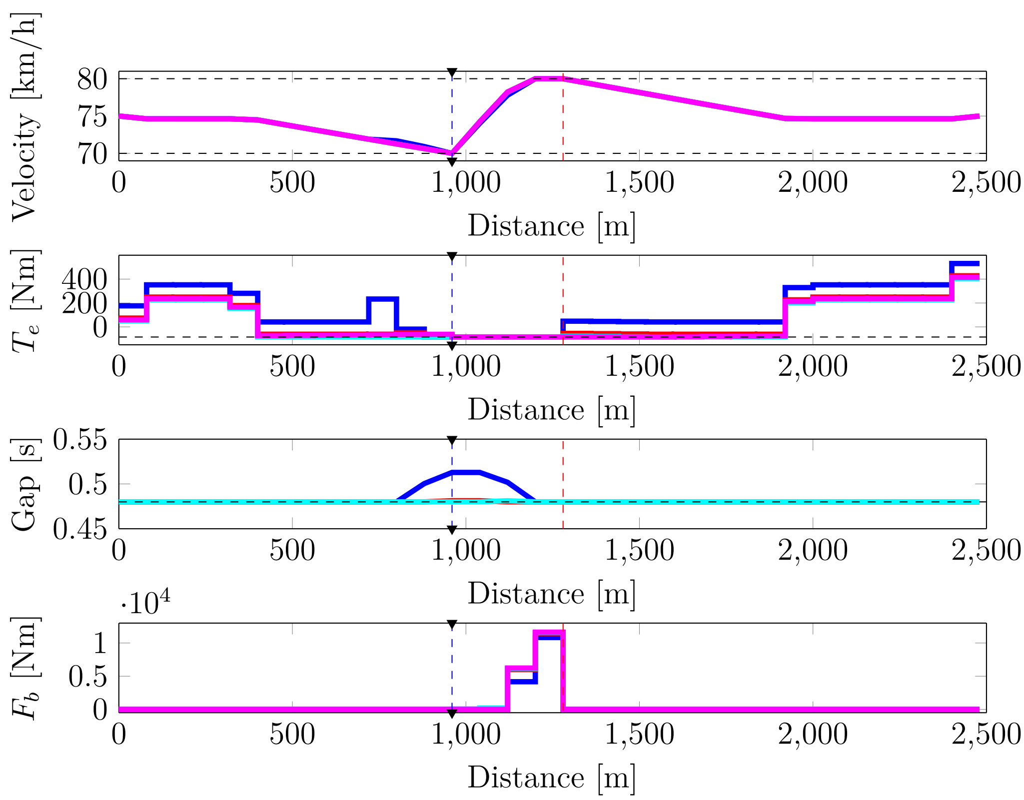

Figure 5.2: Optimal solution with the FKPC using case 2

6
Controller comparisons and parameter changes

In this chapter various results are brought up. First the differences in fuel consumption between the controllers are observed. After this the impact of mass differences is discussed. Results from using different sampling intervals and varying lengths of prediction horizon are also analyzed. Finally the impact of a remodeled air resistance is observed.

6.1 Fuel consumption

This section aims to compare the simulated fuel consumption for the different control structures and analyze the result. Road cases 1, 2 and 4 were used to get an impression of how different road scenarios will impact the result. The data is based on a platoon of four identical vehicles. The controllers PKPC, FKPC and the PPC were implemented and simulated as MPCs in Simulink. Figure 6.1 shows how much fuel each vehicle consumed for case 1.

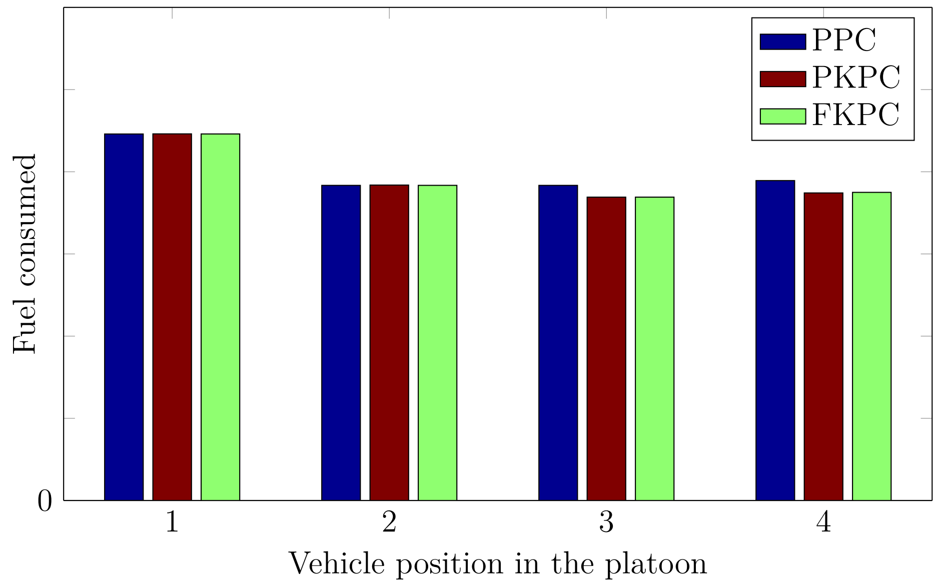

Figure 6.1: Simulated fuel consumption for each vehicle using case 1.

The lead vehicle and the second vehicle's fuel consumption are very similar for all three control methods. The difference in fuel consumption mainly lies in the last two vehicles. The lead vehicle for the PPC calculates its trajectory in the same way as the lead vehicle of the PKPC. This results in the therefore similar. The increased fuel consumption for the last two vehicles in the PPC can be explained by their lack of knowledge of future control actions. This makes the gap controllers react slower to velocity changes in the predecessors compared to the PKPC and FKPC.

The optimal solutions from the PKPC and FKPC are basically the same for case 1. This can be seen from comparing the solutions presented in chapter 4 and 5. This can also be seen in the fuel consumption for the four vehicles.

Figure 6.2 shows the fuel consumption for each vehicle using case 2. Now the effect of the different controllers is more clear. The trajectory for the first vehicle is again the same for the PPC and the PKPC but the fuel consumption is different. This is due to the gap controllers desire to drive close to the predecessor. The lead vehicle in the PPC will then experience a lower air resistance. The second vehicle in the PKPC will increase the distance to the lead vehicle which results in a larger air drag. The gain from increasing the inter-vehicle spacing becomes clear when the fuel consumption for the following vehicles is observed. For these vehicles the PKPC performs better than the PPC. Better still is the FKPC that has a lower fuel consumption for all its members in the platoon.

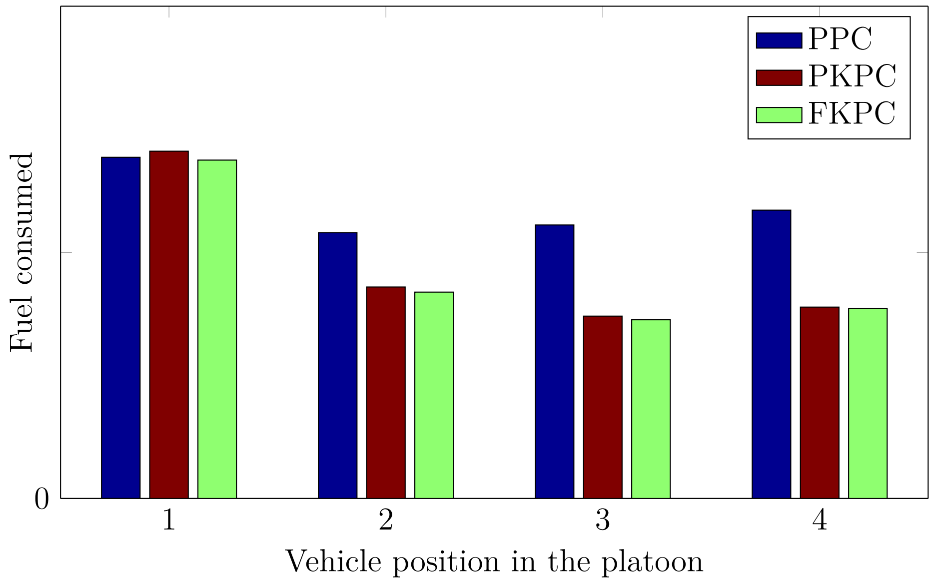

Figure 6.2: Simulated fuel consumption for each vehicle using case 2.

In Table 6.1 the total fuel consumption for the PKPC and FKPC is compared against the PPC. For both road case 1 and 2 the FKPC uses the least fuel but the difference is small for uphill roads. On downhill roads the fuel gain from using more information in the optimization becomes greater.

Table 6.1: Total fuel consumption for the different controllers using hill case 1 and 2

Case	PPC	PKPC	FKPC
1	100%	98.20%	98.21%
2	100%	79.79%	78.15%

The PKPC and FKPC was also run in an MPC simulation for road case 4, the Borås to Landvetter distance. The velocity and inter-vehicle spacing for each vehicle from case 4 is found in the appendix Figure B.1 and Figure B.2. In the simulation the minimum velocity has been lowered. This is because of the long and steep uphill sections that would otherwise be difficult for the HDVs to handle. From the simulation it could be concluded that the vehicles sometimes drive with the smallest allowed separation but both controllers must often increase the separation which is due to the long downhill sections. Both controllers finished with an average velocity only fractions away from the reference. This is merely due to the fact that the actual time and distance traveled was fed back into the control routine and compensated for. For both controllers the vehicles would in the final few hundred meters of the road, drive with a lower than reference velocity to achieve this.

The combined fuel consumption can for case 4 be seen in Table 6.2. As theorized in chapter 5 the first vehicle in the FKPC sacrifices some efficiency so that the combined platoon will gain fuel. This is why the first vehicle is the only one that consumes more energy compared to the PKPC.

Table 6.2: Total and individual fuel consumption for the FKPC compared to the PKPC between Borås and Landvetter

Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Average
100.70%	98.43%	98.01%	98.68%	99.02%

6.2 Heterogeneous vehicles

When a platoon consist of vehicles with different properties it might be advantageous to arrange them in a certain order to spend the least amount of fuel for a particular road section. A platoon of four vehicles, each with a different mass, was used as a basis for this analysis. The optimal fuel consumption for all the 24 different arrangements of the four vehicles was then calculated and compared. The masses used were 20, 33, 46 and 60 tonnes. The results are based on the optimal solution, not the MPC simulations. The topography used to gather the data was case 1 and case 2.

When the FKPC was used the difference in fuel consumption was too small for the arrangement of vehicles to matter. No matter the ordering the optimal solution was always the same. The best way to drive was to keep the inter-vehicle spacing small. The velocity curve would therefor look very similar in all arrangements since the effect from the limiting vehicle will always be the same, no matter the ordering.

The result for the PKPC was similar for both case 1 and case 2 in that for both cases the most fuel efficient order was to place the heaviest vehicle first in the platoon, although it was less important for case 1. The order of the remaining vehicles only altered the consumption marginally. The fuel consumption for the PKPC and all mass combinations can be found in Appendix C

For PKPC using case 1 this result can be explained as follows. When the heaviest vehicle is placed first, its velocity will decrease during the uphill section and it therefore has to increase its speed before the hill in order to maintain the correct average velocity. Since the other vehicles in the platoon are lighter, they can easily follow the same velocity profile. To follow the lead vehicle closely turns out to be the optimal way to drive as this results in reductions in the air drag coefficient. By following the heavier vehicle's velocity trajectory, the lighter vehicles will deviate from their average velocity more than if they were the lead vehicle. These velocity changes will add to the air drag losses for these lighter trucks. The gain of rearranging vehicles in case 1 is therefore not too important since fuel gain for a few vehicles also means losses for other vehicles.

When the heaviest vehicle is not the lead vehicle, the velocity profile for the members in the PKPC platoon will start to differ. An example of this is seen in Figure 6.3. Here the vehicles are ordered from lightest to heaviest.

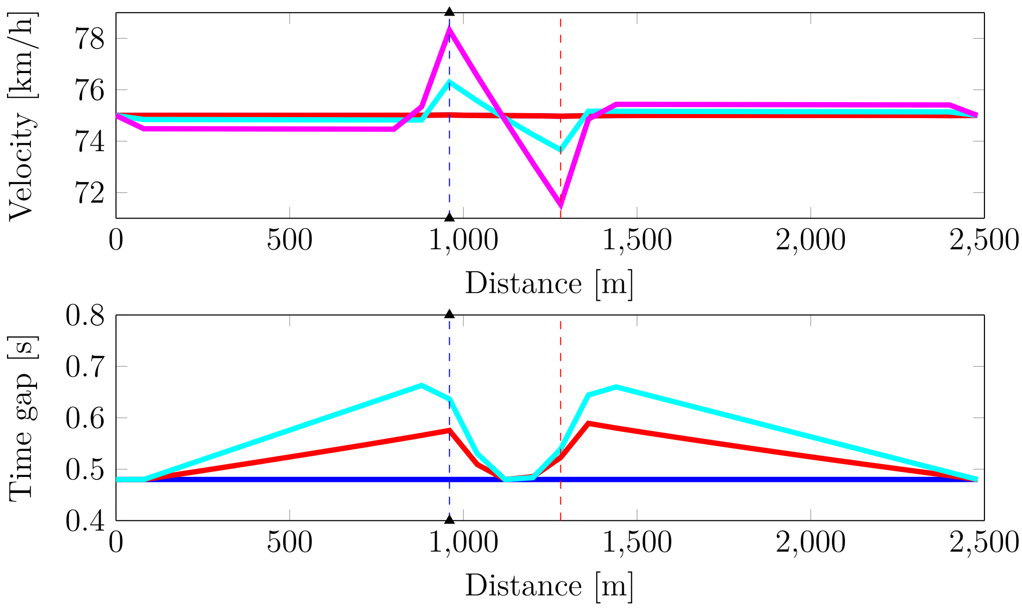

Figure 6.3: Velocity and spacing for a heterogeneous platoon ordered from lightest vehicle to heaviest over an uphill section. First vehicle in blue, second in red, third in cyan and forth in magenta

The first two vehicles can pass over the hill without any change in velocity which causes problems for the remaining two vehicles. The third most heavy truck wants to increase its speed before the hill but this would cause it to get too close to the preceding vehicle. The third vehicle must therefore drive slower for some time in order to increase the inter-vehicular spacing. This leaves room to then accelerate to a higher than average velocity before the hill. After the hill it must now drive with a slightly higher velocity in order to finish the drive cycle within the correct time. The behavior for the last and also heaviest vehicle is similar but the compensatory measures are even greater. All the times where the inter-vehicular spacing is large will of course result in greater air drag and then also a higher fuel consumption.

The fact that the heaviest vehicle should be placed first also for case 2 can be explained as follows. The heavier the truck the faster it will accelerate in a downhill section and the vehicles also wants to decelerate before the downhill section in order to finish with the correct trip time. The heavier the truck the more it must also decelerate before the slope.

If the heaviest vehicle is placed first in the platoon it will, as explained, slow down before the hill. This will in turn force the following trucks to also slow down with the same amount in order to not drive to closely. This then forces the following vehicles to also increase their speed considerably during the remaining trip to compensate for this drop in velocity. The most fuel efficient way to do this is to simply follow the lead vehicle as close as possible.

If the platoon is again ordered after weight with the lightest vehicle first, the result can be seen in Figure 6.4. The lightest vehicle will only decrease its speed slightly before the slope and will then pick up speed in the downhill section. The second vehicle wants to decrease its speed earlier which results in a separation between them which will last the entire downhill section. The same happens for the third and forth vehicle as they must slow down more and more, the heavier the trucks become. The resulting inter-vehicle spacing is what makes this ordering less fuel efficient.

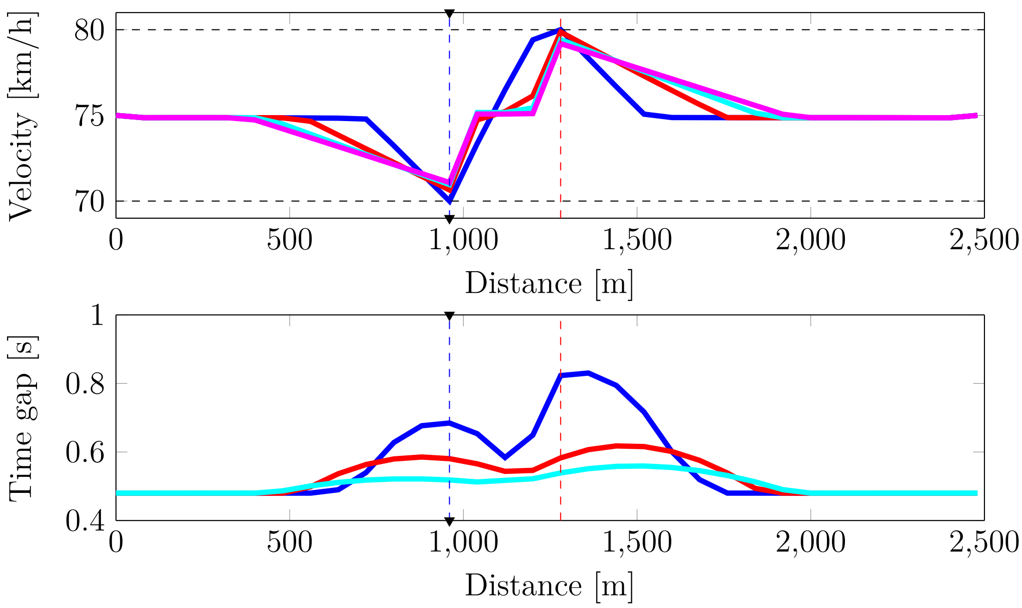

Figure 6.4: Velocity and spacing for a heterogeneous platoon ordered from lightest vehicle to heaviest over a downhill section. First vehicle in blue, second in red, third in cyan and forth in magenta

By ordering the vehicles correctly the fuel consumption can be lowered by 0.18% for case 1 and 12.4% for case 2. Both reductions are for the best case ordering versus the

worst case for the PKPC. One important note is that the average velocity changes slightly depending on the order of the vehicles. This will also affect the overall fuel consumption which makes the calculations less accurate.
For case 1 the average velocity ranged from 74.997 km/h to 75.015 km/h and for case 2 from 75.043 km/h to 75.077 km/h. For the FKPC the variations were also notable with average velocities ranging from 75.012 km/h to 75.015 km/h for case 1 and between 75.080 km/h and 75.097 km/h for case 2.

6.3 Varying sample distance

This section aims to evaluate the difference in results if the sample interval is changed. The results when the sample distance was changed was done from the solution from one FKPC and PKPC optimization. Both case 1 and case 2 was used in those tests.

The five different sample distances used were 10 m, 20 m, 40 m, 80 m and 160 m with a prediction horizon of 2400 m. The difference in fuel consumption for each case is seen in Table 6.3 where a sample length of 160 m is set as reference. From the table it is clear that the gain from faster sampling is minuscule over the uphill section. Both control methods also produce the same solution for this case. This is because the optimum is to follow the predecessor closely which can be done in the same way for both controllers in this specific hill case. The gain from shorter sampling distances comes on the downhill road and here the controllers also produce different solutions.

Table 6.3: Percentage gain in fuel consumption for each controller using different sample lengths and hill topography

Controller	Case	160m	80 m	40 m	20 m	10 m
FKPC	1	0	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$
	2	0	0.84	1.24	1.41	1.5
PKPC	1	0	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$	$< 10^{-3}$
	2	0	2.44	2.96	2.76	2.92

The time it takes to calculate the optimum velocity curve will increase as the sampling distance decreases. This is due to the growth in optimization variables since the accuracy increases but the prediction horizon stays the same. The time it takes will also be influenced on the specific road profile. For the results in this section, the time it took to find the optimum was almost the same when a sample distance of 80 m or 160 m was used. When the resolution was changed to 10 m the required time grew more than 50 times. This means that when the sample distance is to be selected, both processing power and the quality of the result need to considered. The fuel gain from having short sampling intervals is also highly dependent on the topography and it could then be beneficial to decrease the distance on complex situations.

6.4 Varying horizon length

To evaluate the impact of different lengths of prediction horizons the road profile from case 3 was used. Both the PKPC and FKPC was simulated with the ability to know the topography 960 m, 1920 m, 2880 m or 3840 meters in front of them.

The resulting fuel consumption from using different prediction horizons did not differ by a great amount. For the PKPC the largest difference in fuel consumption was less than 0.3% and for the FKPC the largest difference was about 0.4%. With these small variations it is hard to conclude any benefits of using short or long prediction horizons by looking at the fuel consumption alone. The biggest difference in the results lie in the velocity profile. To illustrate this the result for the FKPC is analyzed. The reasoning for the PKPC was very similar and will therefore not be shown.

When the vehicles only had knowledge of the topography 960 m in front of them, the controller would sometimes make more drastic preparations before a hill. In Figure 6.5 this phenomenon is shown for the FKPC with a 960 m prediction horizon. For the first uphill section, at 500 m, the curve looks like usual but when the second uphill section comes the vehicles increase their velocities more than usual as preparation. This is because they can see the coming downhill section and know that they will have to slow down before it. The vehicles must therefore have a high velocity at some point to achieve the correct travel time for this particular part of the road. The vehicles do not see far enough to know that at the end of the downhill road, their velocity will be higher and the earlier increase in velocity is not needed. This is also why they travel with a low velocity after the downhill section.

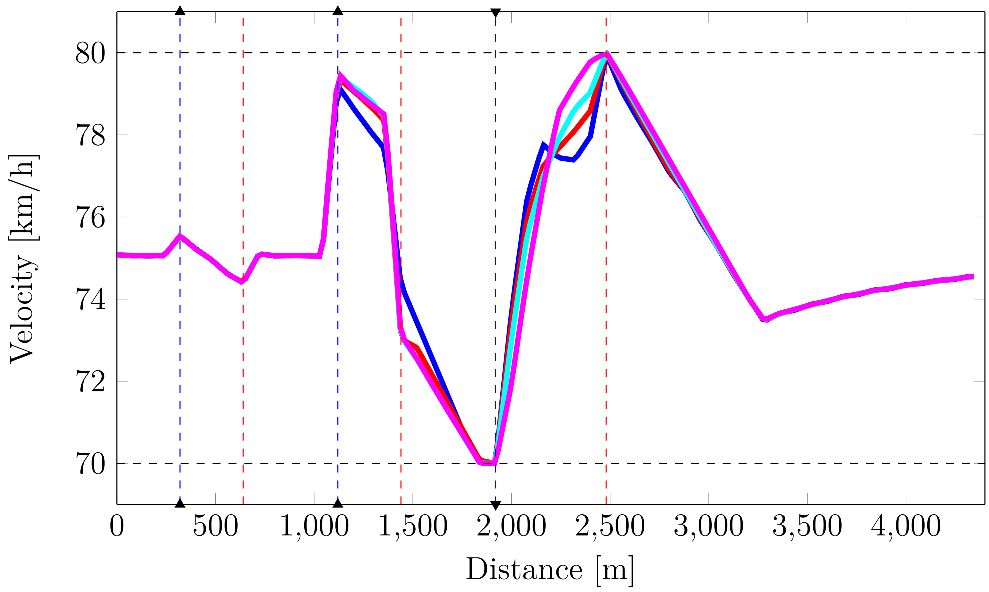

Figure 6.5: Velocities for the FKPC platoon with a prediction horizon of 960 m for road case 3.

In Figure 6.6 where a prediction horizon of 3840 m was used the behavior looks more like one could expect. This time the vehicles keep closer to the average velocity and do not increase the velocity as much before the second uphill. This is since they know that their velocity will be high at the end of the downhill section. The vehicles will also travel closer to the reference velocity soon after the downhill section ends.

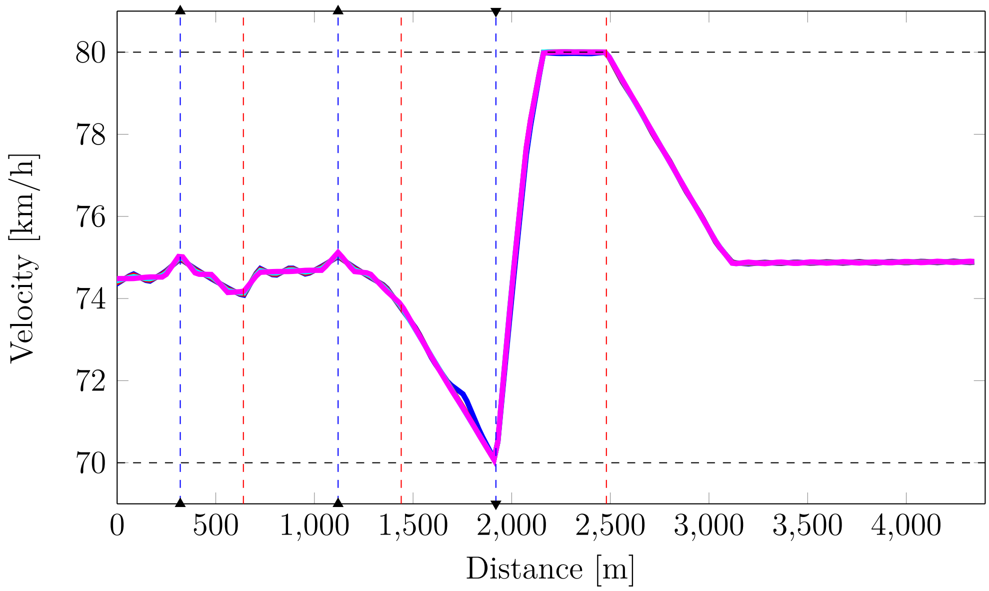

Figure 6.6: Velocities for the FKPC platoon with a prediction horizon of 3840 m for road case 3.

One major factor involved in the decision of horizon length is the computation time. The percentage change in computation time between the two shortest horizons was only a few percent, but when the prediction horizon was extended to 2880 m the computation time was doubled. For 3840 m the required time was around 10 times as great compared to the shortest horizon. The increase in computation time comes from the increase of optimization variables. Also for case 1 and case 2 the same proportions in computation time held true.

6.5 Air resistance

The dynamics of the air resistance is the part of the vehicle model that has the highest uncertainty. It was necessary to make the model simple yet representative but this means that many of the involved factors were overlooked. This chapter is aimed to show how the result would differ if the formula for the air resistance is altered.

First the FKPC was used on both case 1 and case 2 with different K and P values, i.e. the reduction of the air resistance when the inter-vehicle distance is zero and the rate of change when the inter-vehicle distance increases, see Eq. 2.10. In all tests the vehicles continued to stay close together with the smallest allowed separation. The only visible difference was that when the air resistance was lower, the vehicles would decelerate slower if no torque was applied by the engine. This forces the vehicles to start to slow down earlier before a downhill section.

If the air resistance is again lowered on uphill section, less of the engine power is wasted on working against the air resistance. This means that the change in velocity will be smaller over the hill since more power is available to move the vehicles forward. The result will be the opposite if the air resistance is increased, both for uphill and downhill sections.

The result for the PKPC was the same for case 1 as it was for the FKPC. This is since they have the same optimal solution for uphill sections. More interesting for the PKPC is downhill sections since the vehicles will increases their inter-vehicle distance on these roads. Look back at Figure 4.2 for this fact. The length of this separation mainly depends on the difference in air resistance between two vehicles. If the difference is small then the vehicles do not need to separate as much. If the difference on the other hand is larger, a greater separation is required to avoid use of the brake. In Figure 6.7 an example of this is shown for an downhill section. The upper figure shows the normal case when the parameters have not been changed. The lower figure is when the rate of change with respect to separation (the P parameter) has been doubled. The K gain (the static reduction) has been adjusted so that the percentage reduction is the same at the reference separation. This means that the first vehicle do not experience any change.

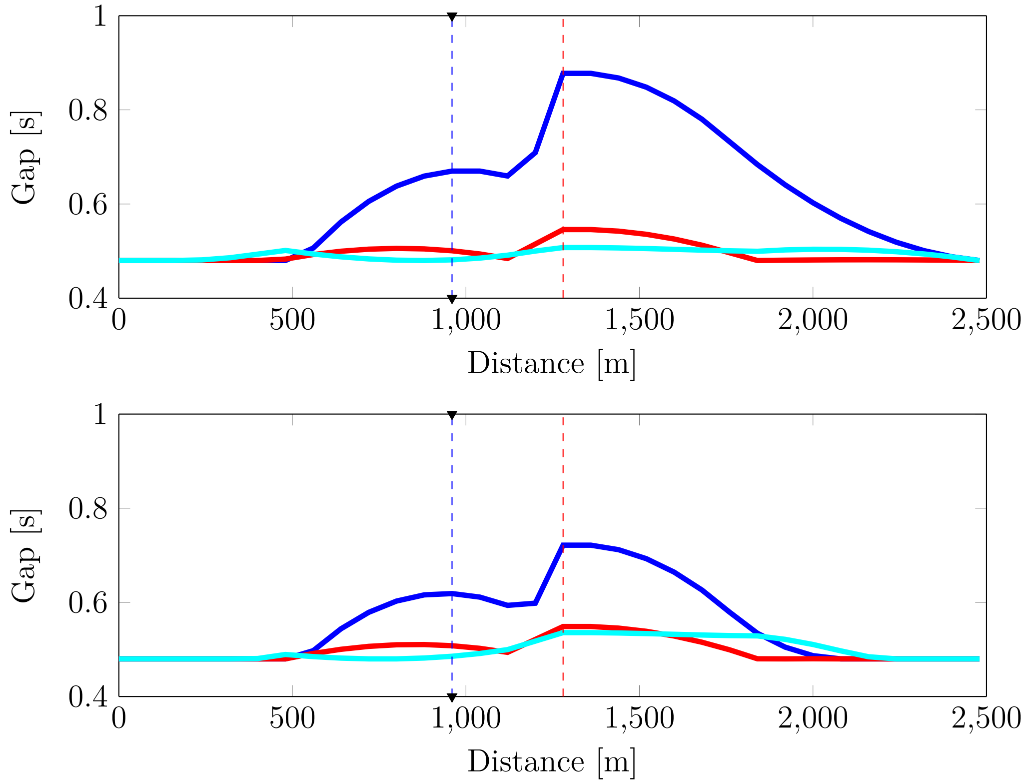

Figure 6.7: The inter-vehicle separation using different rate of change in air resistance over a downhill section. The separation between vehicles 1 - 2, 2 - 3 and 3 - 4 are shown in blue, red and cyan respectively.

The result from the parameter change is that the vehicles do not need to separate as much in order to experience a sufficient increase in air resistance. The difference in time gap is mostly visible between the first two vehicles but this is simply since the parameter change will affect them more because of the previously large gap.

On straight road sections the air resistance stands for more than 70% of the fuel consumption for the first vehicle in a platoon when the air resistance in Eq. (2.9) is used. For the rest of the platoon the air resistance can be contributed to about 60% of the fuel. For non-European trucks and private cars this number is lower due to a more aerodynamic shape of the vehicles. Table 6.4 shows the percentage gain in fuel from driving in a platoon of 4 vehicles compared to 4 vehicles that drive separately. The comparison is done eighth times where the air drag coefficient is decreased 10% each time. The comparison is done on a flat surface to better illustrate the aerodynamic impact.

Table 6.4: Percentage fuel gain from driving in a 4 vehicle platoon compared to 4 individual vehicles for different values on the air drag coefficient.

$1C_d$	$0.9C_d$	$0.8C_d$	$0.7C_d$	$0.6C_d$	$0.5C_d$	$0.4C_d$	$0.3C_d$
21.36%	20.43%	19.39%	18.19%	16.81%	15.19%	13.27%	10.96%

As the table illustrates, both a HDV and a more aerodynamic vehicle will benefit from being part of a platoon.

7
Discussion

In this chapter discussion and thoughts about the project is found. It will end with stating possible future improvements.

7.1 Optimization model

The model of the air resistance is likely the object which has the greatest uncertainty in this project. So far there has been few studies of the reduction in air drag due to having neighboring vehicles. The convex optimization problem can also have negative reductions (increase) of the air drag coefficient. The reductions due to neighboring vehicles should always be greater or equal to zero, see Figure 2.4, but this is something not included in the thesis. This was due to the failure of finding a convex way to state this property. The poor model is unfortunate since the air drag is the only factor that gives benefit from driving in a platoon. The inaccurate air model will likely skew the results presented in this thesis and should therefore be analyzed with some scepticism. Even though the exact figures could be wrong, the general concepts and tendencies presented should still be valid.

The model used to calculate the fuel consumption is not dependant on velocity. This is not true for an actual engine but this simplification was still made. The reasoning was that the velocity of the vehicles should not vary by a great amount. This was more true when hill case 1 and 2 was used, but when simulations for case 4 was run the velocity range grew. This was due to the long up- and downhill sections. It is then possible that the fuel consumption is slightly more or less for those places. Still, the same approximation was done for all control algorithms and errors when the fuel difference between them was compared should then be quite small as they will cancel out to some extent. Another simplification whose impact has not been evaluated much is the time approximation. Again this approximation is near the truth when the velocity range is small but no analysis of its validity has been made for cases where the velocity span is larger.

If the optimization routine is not able to find a solution that can keep the correct average velocity, a slack variable is needed. This could for example happen for long uphill road sections. The cost related to this variable should be appropriately scaled. I some scenarios it might not be important when the platoon arrives. In this thesis the cost was selected large so that the main priority was to keep the correct travel time but this can lead to more extreme optima which is not always wanted.

7.2 Implementation

When the controllers were implemented in Simulink, several calculations had to be made to make the MPCs function correctly. The first is that the FKPC needs to know the velocity that each vehicle will have at the start of each optimization. A new optimization will be done each time the lead vehicle reaches a sample point. The problem is that the following vehicles are still a small distance away from this place in space. This makes it beneficial to predict the velocity of each vehicle at the upcoming position. This is easily done when the vehicles drive in close formation but if the inter-vehicle spacing increases, so does the errors in the velocity prediction. This can cause the controller to find an optimum given an initial condition that will not occur.

A similar problem will occur for the PKPC when the inter-vehicle spacing grows. A vector of predicted times will be sent to a vehicle from its predecessor. This is the basis of this vehicle's optimization. If the distance between the two vehicles is greater than the sample distance, then the received time vector would be based on the next sample point. The vehicle behind would then need to remember the time vector sent from the leader that is based on the previous sample point. This is not a big problem in simulations but it can be in real implementations. The follower will be using old data, one or more sample distance ago. If something were to occur that makes the predecessor change its trajectory so that the predicted velocity curve, based on one point in space, is not being followed at the next sample point, the following vehicle would not be aware of this until it reaches this sample point. It is also possible that this information delay can cause an unstable behavior if the platoon consists of many vehicles that travel with large separations.

The problem with remembering data will also happen for the FKPC. All vehicles except the leader needs to remember the velocity that should be followed at the upcoming sample point. This is as mentioned previously because the trajectory is found when the leader reaches a sample position, but the rest of the platoon has not yet reached this position. If the vehicles have large separations then more than one reference velocity need to be remembered. It is likely that this will cause instability if the separation grows too large.

The gap controllers in the PPC are made out of PID controllers. The main focus in this project was to find an optimization algorithm for optimal platooning. The time spent on finding a stable and well behaved gap controller was therefore short. This is one reason why only few results were compared to the PPC. It simply underperformed and it is expected that the PPC would use less fuel if more time was spent on finding a good gap controller.

7.3 Future work

One relatively easy improvement on the model is a better time approximation. In its current state, the velocity that will have the best time approximation lays close to the reference velocity. For roads where the velocity varies greatly, there is a chance that the approximation is not good enough. This can be solved by calculating the predicted velocity curve for the entire trip beforehand and then find a vector of values that corresponds to the approximation variables at each sample time. By doing this, the approximation can be made accurate as each pair of values in this vector corresponds to a linearization round the predicted velocity along the road. This change would not increase the difficulty of the optimization, except that a large optimization needs to be done before each journey starts.

In this thesis only regular fuel driven HDV's were modeled. A good extension would be to also model hybrid and electric vehicles. This would be an interesting test case as the fuel gain from platooning could be different for these vehicles. This because the vehicles that use an electric engine can recharge their batteries when they use the brake.

Further extensions of the models would be to incorporate gear changes and a velocity depended fuel to torque function. The gear change could be an important factor for roads with steep hills and the engine model is in its current state only good at certain angular velocities.

The model for the air resistance has several possible improvements. Wind speed and side wind is one thing that is not modeled and this will impact the total air resistive force. To get a better model for the drag reduction from driving in a platoon, extensive data gathering is needed from real life testing. It is possible that the model used in this thesis is not accurate.

Implementation changes to make the controllers able to run in real vehicles might be needed. Current HDV's are not designed to transmit a vector of data, such as the vector of predicted travel times. Most common is to send only the current velocity or acceleration. To send more data likely requires the making of a new standard amongst the vehicle companies.

String stability is a behavior that is often discussed in platooning papers. It describes that errors do not propagate through the string of vehicles. String stability has not been evaluated in this thesis but this is something that needs to be done before any real implementation can be made. From observations of the simulation results in the current control algorithms, it is likely that oscillations will start to grow as the number of vehicles increases.

8

Conclusion

By using an intelligent controller in vehicle platoons, the fuel consumption can be lowered. The fuel gains comes mainly from their ability to keep a small inter-vehicle distance between vehicles and by smoothing out the velocity curve over hills. Smoother velocity curves means that the vehicles should increase the velocity as preparation for steep hills and slow down before downhill slopes. The maximum and minimum velocity will then be closer to each other and a lower air resistance is then achieved. It will also minimize the break usage which means that less energy is wasted.

By using a smart control algorithm such as PKPC and FKPC compared to a gap controller the fuel consumption can be lowered but the amount of fuel gained is dependant on the topography. The FKPC was more efficient than the PKPC on downhill sections. On uphill sections the result was similar for both the controllers. For real road data the FKPC would save about about 2% compared to the PKPC. The main reasons for this are that the FKPC has access to more information and V2V communication, which makes it possible for the vehicles to drive with a smaller inter-vehicle distance.

The ordering of heterogeneous vehicles plays a big role for the PKPC where the heaviest vehicle should be placed first in a platoon. The fuel reduction is mostly visible on downhill roads but real terrain will always consist of both up- and downhill sections, and vehicles should therefore be ordered before a journey begins. It can otherwise force vehicles to make large velocity changes to avoid using the brake. This will loose fuel and could be an uncomfortable ride for the passengers.

When the sample distance is to be selected one should, as usual in control algorithms, choose a short length, as long as the computing unit can handle the heavy calculations. This should make sure that the solution is close to the optimal.

The prediction horizon should not be selected too short. If it is then there is a risk that the platoon will overcompensate for predicted future velocity changes to achieve the correct travel time. If the prediction horizon is long, future maneuvers in order to stay within the constraints can be planned more effectively.

The model of the air resistance plays a role in the behavior of the optimal velocity. Depending on the model, the inter-vehicle distance could be different for the PKPC. The FKPC is more robust against a badly modeled air resistance since the vehicles tend to stay in close formation. It can also be concluded that the gain of driving in a platoon will decrease for more aerodynamic vehicles. But even though the fuel savings are smaller, the gain is still several percent which makes it worthwhile.

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A
Model parameters

Table A.1: Values used in the vehicle model

Notation	Description	Value
C_r	Roll resistance coefficient	0.0015
C_d	Air drag coefficient	0.56
ρ	Air density	1.29 kg/m^2
m	Mass of vehicle	40 tonne
g	Gravitational constant	9.81 m/s^2
A	Front area of truck	10.26 m^2
i_f	Final gear ratio	$\approx$ 3.0159
i_c	Transmission gear ratio	1
n_f	Final gear efficiency	1
n_c	Transmission gear efficiency	1
J_e	Engine inertia	3.5 m^2kg
J_w	Wheel inertia	32.9 m^2kg
r_w	Wheel radius	0.5 m

B

Borås to Landvetter simulation

In Figure B.1 and Figure B.2 the velocity and inter vehicle time gap for the road between Borås and Landvetter is shown. The color order is blue for the lead vehicle, red for the second, cyan for the third and the last vehicle is drawn in magenta. The inter vehicle spacing shows the time gap between vehicle 1-2 in red, 2-3 in cyan and 3-4 in magenta.

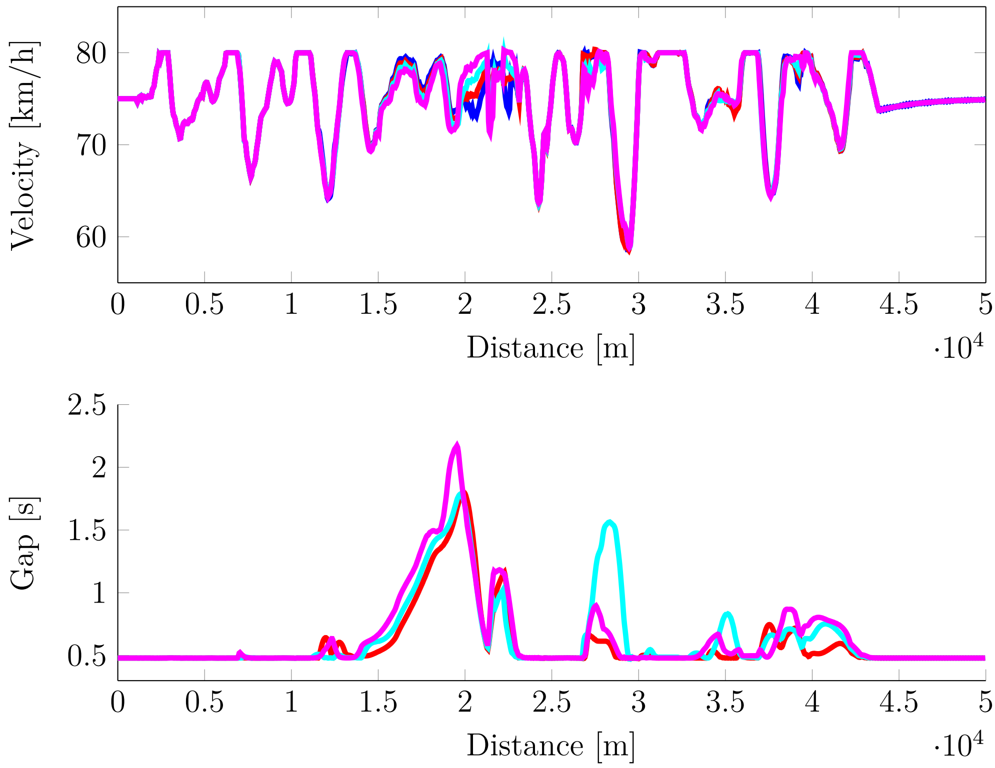

Figure B.1: The velocity and inter vehicle gap from Borås to Landvetter using the FKPC

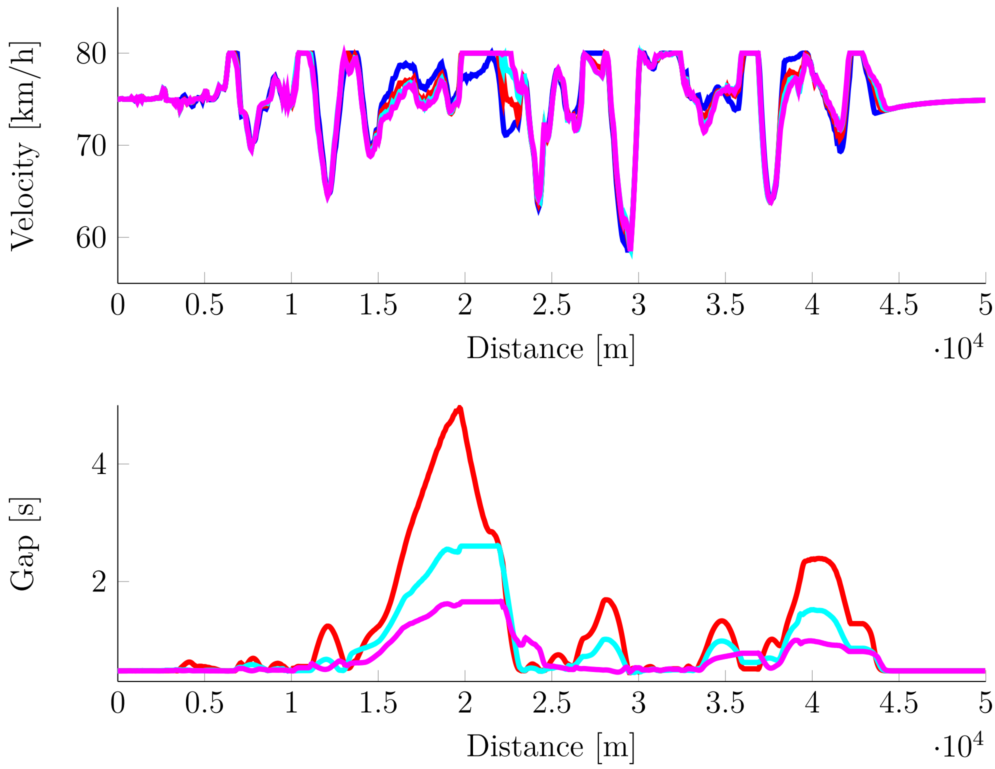

Figure B.2: The velocity and inter vehicle gap from Borås to Landvetter using the PKPC

C

Fuel consumption for a heterogeneous platoon

Table C.1: Average fuel consumption for the PKPC using a heterogeneous platoon. The result is displayed as the percentage change compared to the first vehicle order. The weight order goes from first vehicle to the left and last vehicle to the right.

Weight order	Case 1 [%]	Case 2 [%]
60t46t33t20t	100.00	100.00
60t46t20t33t	100.00	100.00
60t33t46t20t	100.00	100.21
60t33t20t46t	100.00	099.99
60t20t33t46t	100.00	100.03
60t20t46t33t	100.00	100.23
46t60t33t20t	100.06	102.08
46t60t20t33t	100.06	102.10
46t33t60t20t	100.06	102.53
46t33t20t60t	100.05	102.08
46t20t33t60t	100.05	102.16
46t20t60t33t	100.06	102.57
33t46t60t20t	100.14	106.22
33t46t20t60t	100.18	105.89
33t60t46t20t	100.14	106.03
33t60t20t46t	100.18	106.11
33t20t60t46t	100.13	106.37
33t20t46t60t	100.11	106.20
20t46t33t60t	100.18	113.81
20t46t60t33t	100.14	114.17
20t33t46t60t	100.11	113.83
20t33t60t46t	100.13	114.00
20t60t33t46t	100.18	114.03
20t60t46t33t	100.14	113.95