

Gear shift optimization for off-road construction vehicles

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This paper explores the possibility of using recorded road slope data in order to reduce fuel consumption for off-road construction vehicles such as articulated haulers. Road gradients have strong influence on the fuel consumption of a vehicle. This effect is even more significant on construction vehicles due to their large mass and heavy load. In this study, a control algorithm based on model predictive control and dynamic programming is formulated and solved to find an optimal gear shift sequence and time of shifting. The fuel consumption model of an articulated hauler is formulated with a dynamic model and used together with the travel time in the objective function to balance the trade-off between these two aspects. The proposed control algorithm is simulated on a typical road stretch on the construction work site with frequent steep up- and downhill. Simulation shows that both fuel consumption and travel time can be reduced simultaneously. In addition, the optimal gear shift sequence resembles the behaviour of an experienced driver.

***Keywords:** Discrete dynamic programming, fuel efficiency/consumption, gear shift optimization, model predictive control, off-road construction vehicle.*

1. Introduction

Greenhouse gas emissions from the transport sector account for approximately a quarter of the overall greenhouse gas emissions (ECCA, 2010; EPA, 2009). Fuel efficiency has become one of the main focuses for automobile manufacturers in recent years due to the scarcity of fossil resources and stricter environmental policies. Even though the constant development in energy efficient fuel as well as the design of vehicles has succeeded in improving fuel economy during the past decades, increased transport demand is outweighing these benefits. The number of vehicles has increased considerably in many part of the world owing to the rapid economic growth in many developing countries and the rising demand for welfare in industrialized nations.

Driving style together with other variables such as vehicle, engine and fuel types have a significant bearing on the fuel consumption and emission of vehicles. The well-known eco-driving techniques include proper maintenance of the vehicle, reducing the mass and aerodynamic drag, operating the vehicle at the appropriate speed and gear level to obtain the engine's optimum efficiency point, avoiding sudden starts and stops, accelerating quickly and smoothly as well as decelerating gradually when it is necessary, anticipating the surrounding environment, and so on. Barkenbus (2010) reported that these fuel efficient driving techniques reduce fuel consumption by 10% on average. A study using 19,230 driving patterns collected in real traffic was carried out by Ericsson (2001) to identify independent driving pattern factors and

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their effect on emissions and fuel consumption. Statistical analysis showed that nine factors are of great importance for the fuel use and emissions. Among the nine factors, four of them are related to acceleration and power demand, three factors describe aspects of gear changing behaviour and two are associated with the speed level of the vehicle.

A vehicle simulator developed by the National Renewable Energy Laboratory in the U.S. was described by Markel et al. (2002). This simulator is primarily used as an analysis tool to quantify the fuel economy as well as the performance and the emissions of vehicles, and it is assumed that speed is the only factor that determines a vehicle's performance. Saboohi and Farzaneh (2009) argued that considering only the vehicle speed in the calculation of fuel consumption has certain drawbacks, and is not sufficient for the analysis of eco-driving rules. Thus they proposed a model of the optimal driving strategy which minimizes fuel consumption as a function of speed, gear ratio and engine load.

Fuel consumption is greatly influenced by road gradients. Researchers have made a number of attempts to develop fuel usage reduction methods with the help of information concerning road terrain. Schwarzkopf and Leipnik (1977) made the first attempt and proposed an optimal control problem employing feedback control to minimize the fuel consumption under various road conditions. A highly simplified mathematical model for vehicle fuel consumption was formulated and solved using the Pontryagin maximum principle. Schwarzkopf and Leipnik concluded that a steady state velocity minimizes the vehicle's total fuel usage on level ground. For uphill slopes, the authors suggested acceleration in order to gain speed just prior to reaching an uphill and then to allow the speed to drop while climbing the hill. They also indicated that a reverse behaviour is appropriate for a downslope.

A better accuracy of fuel usage calculation was obtained in (Hooker, 1988) by combining a fuel consumption simulator and dynamic programming technique to solve the fuel optimal control problem. The experiment was carried out using real vehicles running on test tracks or on-road to obtain extensive statistics. Four special cases of the fuel optimal control problem were investigated: cruising on level road, accelerating to cruising speed, driving between stops, and driving over hills. Hooker came to the same conclusion as Schwarzkopf and Leipnik that constant speed is the optimal solution for fuel economy on level roads. The author pointed out that fuel economy is rather sensitive to the way one drives between stops and over hills, and the potential fuel savings are significant in these two cases. For driving on uphill and downhill grades, the experiments showed that fuel economy tends to be intensive to speed, especially on steeper grades. The author thus recommended acceleration before reaching an uphill to compensate the speed loss while ascending the hill. The reported savings of constant-speed driving versus optimal control over hills in the experiment were quite substantial; constant-speed driving consumed on average 7% more fuel on a 3% grade slope and 18% more on a 6% grade. However, the difference between the total travel times spent with constant-speed driving and the optimal driving over hills were not mentioned.

Chang and Morlok (2005) studied the optimal speed profiles for rail vehicles to minimize work and fuel consumption. They argued that the previous studies on optimal vehicle speed control required detailed analysis on both the vehicle and its driveway profiles. Thus, it normally required complex methods to solve the problems analytically and the results were often unique to each problem. They proposed a guideline for deriving the optimal speed for road and rail transportation in general. The derivation relied on the proportionality between the fuel consumption and the produced work, the vehicle resistance of the quadratic form, the energy conservation, and the relatively long distance travelled between stops. This guideline reached a closed form solution that constant speed minimizes fuel consumption and propulsive work. This result was confirmed using a train performance simulator.

Using a realistic model of a truck powertrain, Fröberg, et al. (2006) studied the fuel optimal speed profiles for heavy trucks on three different topographic road profiles: level road, small gradients,

and steep gradients. They derived explicit analytical solutions and showed that constant speed is optimal on level road and with relatively small gradients. For steep downhill slopes, it was optimal to utilize the vehicle's kinetic energy to accelerate through the road section. However, the authors also pointed out that it is necessary to reduce the fuel injection at a point before the downhill to prevent the vehicle's velocity from exceeding the maximum speed limit.

The advancement of new information and sensing technologies has made significant progress in improving transport efficiency and safety. In recent years, several studies have been carried out to examine the possibility of improving fuel efficiency utilizing road topography information and Global Positioning System (GPS). Hellström, et al. (2006) developed a Model Predictive Control (MPC) scheme to control the longitudinal behaviour of a heavy diesel truck to minimize its fuel consumption. Utilizing a known 3D road map and the current heading of the vehicle received from a GPS unit, the MPC algorithm determined the acceleration and brake level, as well as the selected gear. Weighting parameters were introduced to combine fuel usage, travel time and deviation from the reference velocity into a single objective function. A discrete dynamic programming technique was employed to solve the optimization problem numerically. The optimization scheme was demonstrated using computer simulation and the result showed that the fuel consumption of a drive mission can be reduced by 2.5% without significant changes in travel time. Subsequently, this MPC fuel optimization approach was further improved for online implementation by Hellström, et al. (2009) and evaluated with a real truck on several highway segments in Sweden. The experiment results showed an average reduction in fuel consumption of 3.5% compared to a standard vehicle cruise control without increasing travel time. Additionally, the number of gear shifts was decreased by approximately 40%.

Ivarsson, et al. (2009) studied the fuel consumption optimization problem for heavy trucks utilizing the road slope information and with a known combustion engine fuel consumption map. The authors reasoned that since the fuel consumption of an engine has a nonlinear relation between its speed and the resulting torque for the same fuel injection, it is thus more beneficial for certain points than others in the fuel consumption map. Computer simulation confirmed that the fuel consumption can be reduced by approximately 1%.

However, these methods have not yet been investigated on off-road vehicles such as construction equipment due to unavailability of 3D maps of the operating environments. Construction equipment is in general very fuel-consuming machinery because of its large mass and its heavy load of construction materials. A decrease of few per cent in fuel usage can give a substantial cost reduction. Although development engineers are working constantly to optimize the design of the machines with regard to their overall performance and fuel usage, there are still improvement that could be made with the help of new sensing and information technologies such as GPS and road topographical information.

This paper explores the possibility of using recorded road topography information together with a GPS unit to minimize fuel consumption and travel time for off-road construction vehicles. An optimal control algorithm based on model predictive control (MPC) and dynamic programming (DP) is formulated. Optimal control of vehicle fuel consumption depends on many different factors of the vehicle and the driving environment, and it would not be possible to compute solutions for every possible situation. The gear ratio and the time of shifting are identified as control variables in this study. The proposed MPC controller uses a model of the vehicle dynamics and the recorded road slope data to predict the future values of certain relevant states over a limited position horizon just ahead of the vehicle. These predicted states are then utilized in a discrete dynamic programming algorithm to find an optimally timed sequence of gear shifts as a function of the future vehicle position for the particular prediction horizon. Optimality is here considered in the sense of both fuel consumption and travel time. The optimal gear shifting rules obtained in this study are intended for implementation in the control rules for automatic clutching and ultimately online application.

The optimization algorithm is applied to a model of an articulated hauler (Figure 1). The paper is organized as follows. In Section 2, we present a dynamic model of a hauler manufactured by Volvo Construction Equipment (Volvo CE) and its fuel consumption model. The proposed control algorithm is explained in Section 3. Section 4 shows the simulation results and the gear shifting behaviour is graphically illustrated, compared and analysed. Finally, conclusions are drawn in Section 5.

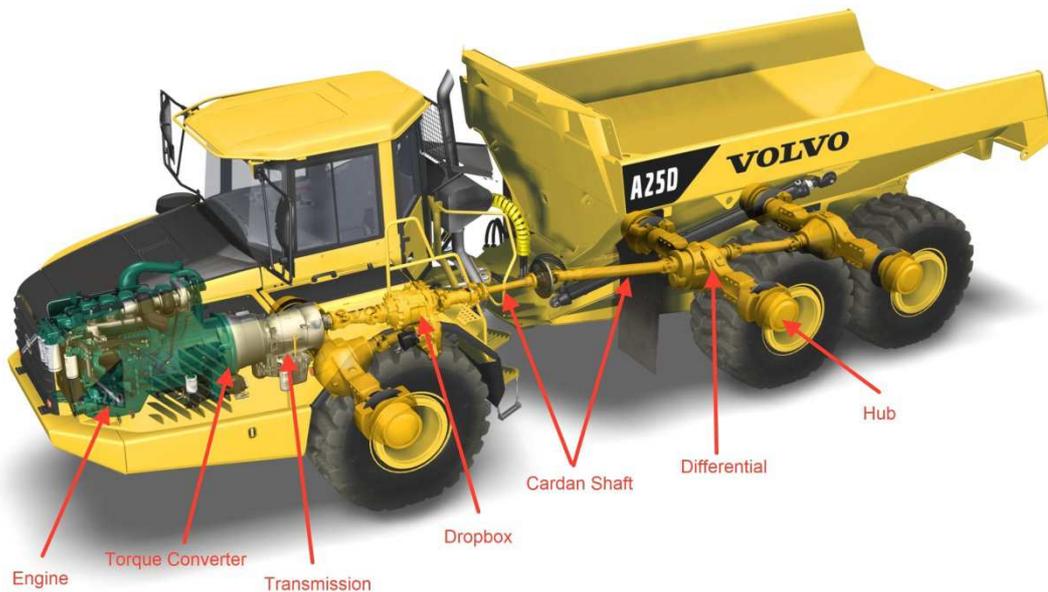


Figure 1. An articulated hauler

2. Vehicle Dynamic Modelling

Articulated haulers are the most commonly used off-road vehicles and are employed for transportation purposes between working stations on construction sites. The powertrain model of Kiencke and Nielsen (2005) serves as the inspiration for the dynamic model of an articulated hauler derived in this section. Modifications are made to model the hauler's driveline. The powertrain for a motor vehicle includes an engine and a driveline. The engine converts fuel into motion and the driveline transfers torque and angular velocity from the engine to the wheels according to the efficiency and gear ratio. Normally, the driveline consists of a clutch, transmission, shafts, differentials and wheels. For certain automatic transmission vehicles like articulated haulers, the clutch is replaced by a torque converter and a lockup for improved efficiency. Figure 2 illustrates the powertrain of an articulated hauler. The powertrain components are represented as virtual systems blocks which indicate interaction of energy through various parts of the vehicle system.

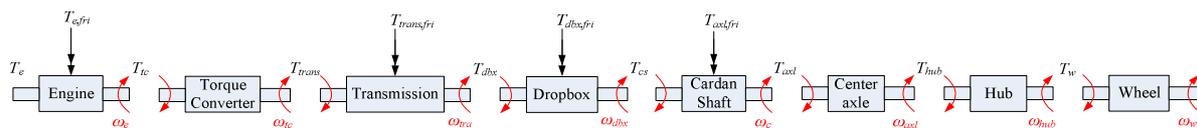


Figure 2. The powertrain of articulated hauler

The diesel engine of an articulated hauler is equipped with a turbocharger that boosts the engine's horsepower without significantly increasing its weight. The torque T_e generated by the engine together with the turbocharger depends on the fuel input level u_f and the engine speed ω_e ,

$$T_e = f_e(u_f, \omega_e) \quad (1)$$

The output torque of the engine is represented by the driving torque T_e resulting from the combustion, the internal friction and the external load from the torque converter T_{tc} . Newton's second law of motion gives the following relation,

$$J_e \dot{\omega}_e = T_e - T_{e,fric} - T_{tc} \quad (2)$$

where J_e is the mass moment of inertia of the engine and $T_{e,fric}$ is the internal friction from the engine.

The angular velocity of the engine is transformed to the wheels via shafts and differentials with various gear ratios. This relation is expressed by $\omega_w = i_{trans}(g_k) i_{axl} i_{hub} \omega_e$, where $i_{trans}(g_k)$, i_{axl} and i_{hub} are the conversion ratios for transmission, centre axle and hub respectively, and $i_{trans}(g_k)$ depends on the current gear g_k . The vehicle speed v is the product of the wheel radius r_w and its rotation speed ω_w

$$v = r_w \omega_w \quad (3)$$

Hence, the following relation between vehicle speed and engine speed holds

$$v = \frac{r_w}{i_{trans}(g_k) i_{axl} i_{hub}} \omega_e \quad (4)$$

2.1 Resisting forces

The main resisting forces in the vehicle's longitudinal direction are aerodynamic drag F_a , rolling resistance F_r and gravitational force F_g . The air drag is estimated by

$$F_a = \frac{1}{2} c_w A_a \rho_a v^2 \quad (5)$$

where c_w is the air drag coefficient, A_a the maximum vehicle cross section area, and ρ_a the air density. The rolling resistance F_r is approximated by

$$F_r = c_r F_N = c_r mg \cos(\alpha) \quad (6)$$

where c_r is the rolling resistance coefficient, F_N the normal force of the vehicle on the tires, m the mass of the vehicle, g the gravitational acceleration and α the slope of the road. Finally, the gravitational force is obtained as

$$F_g = mg \sin(\alpha) \quad (7)$$

Newton's second law of motion governs the vehicle dynamics as a point mass in the longitudinal direction

$$m\dot{v} = F_w - F_a(v) - F_r(\alpha) - F_g(\alpha) \quad (8)$$

2.2 Fuel consumption

The mass flow of fuel \dot{m}_f is determined by the fuelling and engine speed as

$$\dot{m}_f(\omega_e, u_f) = c_f \omega_e u_f \quad (9)$$

where c_f is a lumped parameter that depends on the number of cylinders and number of crankshaft revolutions per stroke. Using the relation (4) between the vehicle speed and angular velocity of the wheel, we rewrite the mass flow of fuel as a function of the vehicle speed v and throttle input u_f

$$\dot{m}_f(v, u_f) = c_f \frac{i_{trans}(g_k) i_{axl} i_{hub}}{r_w} v u_f \quad (10)$$

The fuel consumption for a time interval $[t_0, t_f]$ is then the integral of the mass flow

$$m_f = \int_{t_0}^{t_f} \dot{m}_f(v, u_f) dt \quad (11)$$

2.3 Complete Driveline Model

Fundamental equations for the driveline are derived by employing the generalized Newton's second law of motion and the relations between inputs and outputs in each component in Figure 2. We obtain the expression for the complete driveline model

$$\dot{v} = \frac{r_w}{mr_w^2 + J_{lumped}} \left(i_{lumped} \eta_{lumped} T_e(v, u_f) - T_B - r_w (F_a(v) + F_r(\alpha) + F_g(\alpha)) \right) \quad (12)$$

where

$$\begin{aligned} i_{lumped} &= i_{trans}(g_k) i_{axl} i_{hub} \\ \eta_{lumped} &= \eta_{dbx} \eta_{axl} \eta_{hub} \\ J_{lumped} &= i_{hub}^2 \eta_{hub} \left(\eta_{axl}^2 \eta_{axl} \left(\eta_{dbx} \left(i_{trans}^2(g_k) \eta_{trans} J_e + J_{trans} \right) + J_{dbx} \right) + J_{axl} \right) \end{aligned}$$

In equation (12), T_B is the brake torque and η is the efficiency coefficient for the corresponding component. The dynamic vehicle model is descriptive enough to accurately represent the longitudinal motion of the vehicle and its fuel use, but also simple enough to enable real-time application. The validity of this model has been verified by comparison with data from Volvo CE's in-house simulation software.

3. Control algorithm

A numerical approach is employed to solve the on-line optimization problem. For that reason, the prediction model of the system dynamics needs to be discrete. Furthermore, the vehicle driveline model is transformed from being parameterized by time to being parameterized by position since the recorded road inclination data and GPS coordinates are position related:

$$\frac{dv}{dt} = \frac{dv}{ds} \frac{ds}{dt} = \frac{dv}{ds} v \Rightarrow \frac{\Delta v}{\Delta t} = \frac{\Delta v}{\Delta s} v \Rightarrow \Delta t = \frac{\Delta s}{v} = \frac{h}{v}, v \neq 0$$

The vehicle motion is formulated in equation (12) where the vehicle speed, fuel consumption and the engaged gear are the system states, $\mathbf{x} = [v \ m_f \ g]^T$. The control signals \mathbf{u} are fuelling u_f , brake torque u_B and gear selection u_g . In fact, the first two signals, fuelling and brake are controlled by the driver and the control algorithm can only regulate the gear selection u_g . Finally, the system dynamics are given as

$$\begin{aligned} \dot{v} &= f_1(\mathbf{x}, \mathbf{u}, \alpha) \\ y_1 &= v \\ y_2 &= m_f = f_2(\mathbf{x}, \mathbf{u}) \end{aligned} \quad (13)$$

where $\mathbf{u} = [u_f \ u_B \ u_g]^T$, f_1 and f_2 are given in equation (12) and (11) respectively.

In equation (12), the throttle, brake input and gear choice are the control signals. We mentioned previously that the throttle and brake are actually decided by the driver. The behaviour of the driver in this work is modelled by a constant throttle input and zero brake input. Furthermore, the selected gear and the road inclination are assumed to be constant in each discretization interval. The travel distance is divided into N steps with step length h_k . Using Euler's integration method with the step length h_k , we discretize the velocity and the mass flow of fuel as

$$\begin{aligned} v_{k+1} &= v_k + \Delta t_k f_1(\mathbf{x}_k, \mathbf{u}_k, \alpha_k) = v_k + \frac{h_k}{v_k} f_1(\mathbf{x}_k, \mathbf{u}_k, \alpha_k) \\ m_{f,k+1} &= m_{f,k} + \frac{h_k}{v_k} f_2(\mathbf{x}_k, \mathbf{u}_k, \alpha_k) \end{aligned} \quad (14)$$

where \mathbf{x}_k is discretized states.

3.1 Objective function

The main objective in this study is to minimize the fuel consumption utilizing the knowledge of the road slope of the vehicle obtained from GPS localization and a 3D map. However, narrowly minimizing the fuel use will eventually lead to an increased travel time. Hence, a weight function (15) with scalar penalty parameters β for fuel usage and $1 - \beta$ for trip time, with $\beta \in [0, 1]$, is introduced to balance the trade-off between these two perspectives. In reality, the balance between fuel consumption and time usage is a factor that should be tested and determined by the user.

$$\zeta_k = \beta m_{f,k} + (1 - \beta) t_k \quad k = 0, 1, 2, \dots, N - 1, \quad \beta \in [0, 1] \quad (15)$$

3.2 Control constraints

The road conditions for articulated haulers are usually very rough and often consist of steep up- and downhill slopes. For this reason, the vehicle velocity can vary drastically during a drive. With a full load, steep hill and rough terrain conditions, the vehicle usually travels with very low speed. Hence, the lower bound of vehicle speed is set to zero,

$$0 < v \leq v_{\max} \quad (16)$$

The engine speed limits vary with different hauler models, and the one we are studying is the model A25D from Volvo CE with configuration 6x4 or 6x6 operator selectable drive modes. The engine operating range for this model is [600, 2300] rpm and the preferable range is [1000, 2100]

rpm. In the ranges of [600, 1000] and [2100, 2300] rpm, the engine will still operate even though low engine speed will cause vibration and high speed leads to overheating. Operating in unfavourable conditions wears out the engine and shortens the expected life time of the various components. Hence, a “soft” constraint on engine speed will be used in the optimization problem,

$$\omega_{\min,soft} = 1000 \leq \omega_e \leq \omega_{\max,soft} = 2100 \quad (17)$$

The haulers of model A25 are equipped with a 6-gear automatic transmission and the gear shifts are sequential, *i.e.* there is no skipping of gears. For example, to get from the first gear to the third, one has to go through the second gear. The same is true for downshifting. The mathematical expression for this constraint is

$$g_k \in \begin{cases} \{1, 2\} & \text{if } g_{k-1} = 1 \\ \{5, 6\} & \text{if } g_{k-1} = 6 \\ \{g_{k-1}, g_k, g_{k+1}\} & \text{otherwise} \end{cases} \quad (18)$$

A manual transmission locks and unlocks different sets of gears to the output shaft to achieve various gear ratios. An automatic transmission on the contrary uses a set of planetary gears to produce all of the different gear ratios. Moreover, an automatic transmission uses a fluid-coupling torque converter to replace the clutch in order to avoid engaging/disengaging clutch during gear changes. There are torque limits in some gear shifts leading to some loss in torque during a shift, and the vehicle speed will hence drop during gear shifts. Therefore, frequent gear changing is neither possible nor desirable. The time needed for a gear shift depends on the current gear and the vehicle speed. Generally, shift time is shorter for higher gears and higher velocities than for lower ones.

To begin with avoiding frequent shifts, the obvious hasty shift sequences like up-down and down-up in two subsequent discretization stages are eliminated from the possible gear shift search space. For example, shift sequences like [1, 2, 1] and [2, 1, 2] are not allowed. In addition to the previous constraints on g_k , we require that

$$u_{g,k} \in \begin{cases} \{0, 1\} & \text{if } g_{k-1} > g_{k-2} \\ \{-1, 0\} & \text{if } g_{k-1} < g_{k-2} \\ \{-1, 0, 1\} & \text{otherwise} \end{cases} \quad (19)$$

3.3 The Optimal Control Problem

To summarize, the optimal control problem can be formulated as

$$\begin{aligned}
 \min \quad & \sum_{k=0}^{N-1} \zeta_k = \sum_{k=0}^{N-1} \beta m_{f,k} + (1-\beta) \frac{h_k}{v_k} \\
 \text{subject to} \quad & v_{k+1} = v_k + \frac{h_k}{v_k} f_1(\mathbf{x}_k, \mathbf{u}_k, \alpha_k) \\
 & m_{f,k+1} = m_{f,k} + \frac{h_k}{v_k} f_2(\mathbf{x}_k, \mathbf{u}_k, \alpha_k) \\
 & g_{k+1} = g_k + u_{g,k} \\
 & 0 \leq v \leq v_{\max} \\
 & \omega_{\min,soft} \leq \omega_e \leq \omega_{\max,soft} \\
 & \beta \in [0,1] \\
 & u_{g,k} \in \begin{cases} \{0 \ 1\} & \text{if } g_{k-1} > g_{k-2} \\ \{-1 \ 0\} & \text{if } g_{k-1} < g_{k-2} \\ \{-1 \ 0 \ 1\} & \text{otherwise} \end{cases}
 \end{aligned} \tag{20}$$

3.4 Solution Algorithm

A model predictive control strategy is applied to solve this fuel optimization problem. MPC is an iterative model-based optimal control technique which minimizes a cost function subject to system dynamics and constraints involving states and controls at each time step (Camacho and Bordons, 2004). The model predictive control problem is typically formulated as solving an on-line finite horizon optimal control problem that can incorporate knowledge of future conditions as well as constraints of the system. This method has recently gained considerable attention on account of the increased speed and memory capability of modern microprocessors.

In the MPC scheme, the current state of the underlying system at the discretization stage k is sampled and the controller determines the inputs such that an objective function is optimized with dynamic programming over a prediction horizon S_p into the future. After the optimal strategy over horizon S_p has been determined, the first steps of the control strategy are implemented over a shorter horizon S_c . The state of the system dynamics is measured again and the whole procedure—prediction and optimization—is repeated to obtain new control inputs with the prediction and control horizons shifted forward. Figure 3 illustrates the concepts of prediction horizon and control horizon in this optimal control problem.

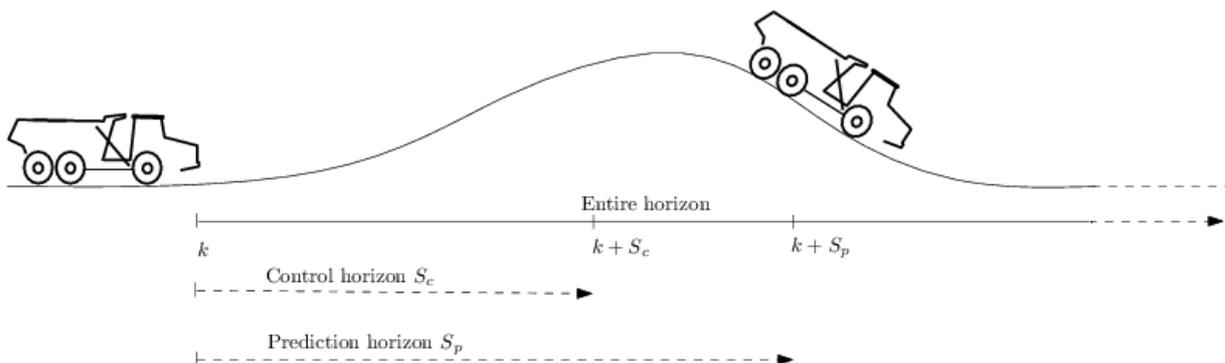


Figure 3. Illustration of the model predictive technique

One could argue that the control strategy can be applied over the entire horizon. Unfortunately, finding a simple model that perfectly represents the system dynamics appears to be impossible in practice, and disturbances also need to be taken into account. Due to model-system mismatch and disturbances, the true system behaviour is different from the predicted system. The model does however provide a good approximation of the actual system over relatively short prediction horizons.

3.5 Algorithm Enhancement

In this optimization problem, gear selection and vehicle velocity are the state vectors, and the 2-dimensional state space is illustrated in Figure 4. Each point in stage k in Figure 4 consists of a unique combination of a velocity and a gear number. The possible number of states is determined by the velocity range, the uniform velocity discretization step δ and the number of possible gears. Thus, the maximum number of states at each stage with 6-gears transmission will be $\frac{6v_{\max}}{\delta}$, which is a large number even though the maximum speed for hauler model A25 is approximately 50 km/h. The total number of paths from the first stage to the last stage is even greater and grows exponentially with the number of states.

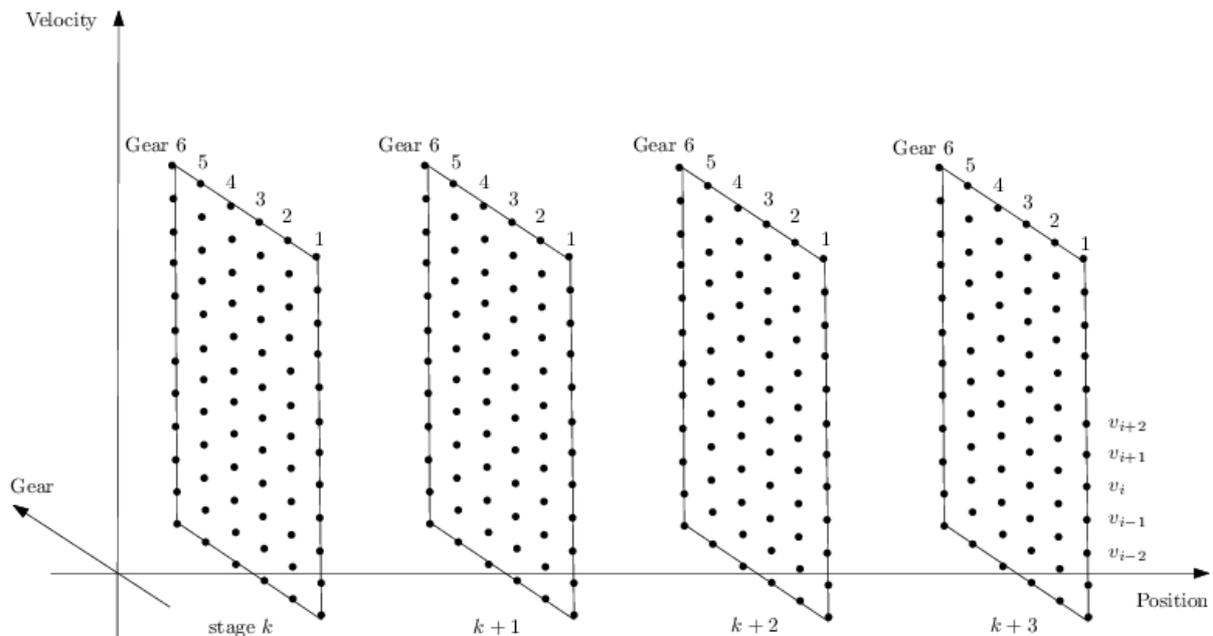


Figure 4. State space

The number of states at each stage has to be reduced to guarantee an effective optimization algorithm. Control constraints (17)-(19) will make the first contribution in the gear state space reduction. In spite of these constraints, the allowed velocity space is still large and further reduction is yet necessary. This is done by calculating a reachable velocity range from the given initial state over the actual prediction horizon shown in Figure 5. At the beginning of each prediction horizon, a relatively small velocity difference v_ϵ is added to the initial velocity v_0 . As we mentioned earlier, the predicted system states might differ from the real ones due to model-system mismatch and disturbance. Thus v_ϵ is added here so that we do not eliminate possible states in the search space. We use the velocity $v_0 + v_\epsilon$ as the initial value and apply the vehicle dynamics together with the road information while choosing the gear that gives the maximum velocity for each iteration step. A new upper bound for the speed over this prediction horizon is

then obtained, see the blue line in Figure 5. Analogously, a lower bound for the speed (the green line in Figure 5) is calculated by selecting the gear which gives the lowest velocity in each iteration step starting from the reduced initial velocity $v_0 - v_\epsilon$. Hence, we obtain a bounded velocity limit $[v_{\min,b}, v_{\max,b}]$ for the prediction horizon.

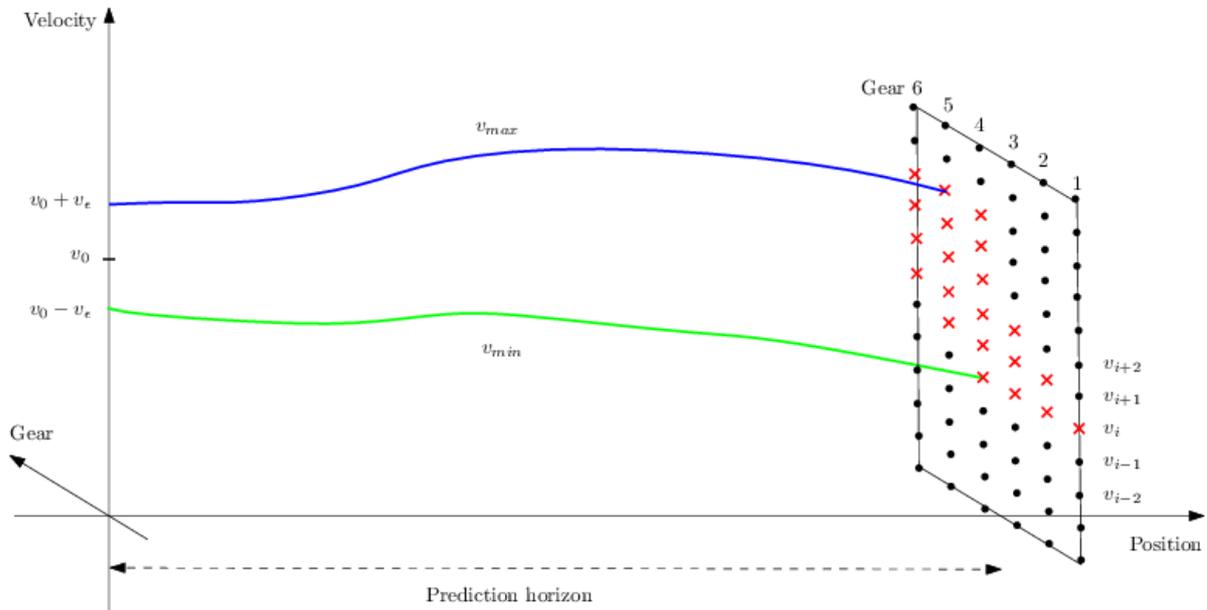


Figure 5. The bounded velocity range

In consideration of eventual model errors in the system dynamics, the limits of the preferable engine speed constraints are relaxed to the engine's operating range (a "hard" constraint) when calculating the bounds on speeds

$$\omega_{\min,hard} \leq \omega_e \leq \omega_{\max,hard} \quad (21)$$

For a given vehicle speed, only a group of gears is feasible. When the last stage of the prediction horizon is reached, all feasible gears for the velocities within the new range will be selected using the soft engine speed constraint (17). In this way, the feasible search space at the last stage of the prediction horizon is chosen (see the red crosses in Figure 5). These states are then utilized in a DP algorithm to find an optimal gear shift sequence for the current prediction horizon.

The step length h_k is an interesting parameter that is worth giving some attention. The control signal of gear selection is constant in every discretization step h_k . Long step length will produce long prediction and control horizons, and the DP algorithm will therefore not be repeated frequently for a given road section. The downside of long step lengths is that steep and frequently changing road slopes may cause the DP algorithm to not find a solution. One could deal with this problem by shortening the step length so that it is possible to shift up or down without delay in tough road situations. The negative effect is lower efficiency, as the DP algorithm will be applied more frequently compared with long step length. Besides, the computational complexity increases as the number of stages is expanded.

The DP algorithm's feasibility and efficiency is improved by varying the step length for different road slopes. When starting from the initial stage in each prediction horizon, the horizon is divided in N stages with step length h_k such that it is possible for the DP controller to find solutions for relatively small road slopes. While computing the narrower velocity range

$[v_{\min,b}, v_{\max,b}]$ at each stage, the position discretization step length h_k will be split into even smaller steps if the absolute value of road slope is large, and the length of new discretization step depends on the absolute value of road slope. The larger the road slope is, the finer is the discretization grid. The reference values of road slope and a suitable discretization grid are obtained by testing vehicle dynamics until a feasible solution is found.

Taking the road slope influence on vehicle velocity into consideration, the possible search space can be further reduced. Intuitively, vehicle speed will drop when driving uphill and will increase during a downhill, for a constant fuel injection. The magnitude of the road slope also affects the vehicle speed differently. Steep uphill will result in more velocity decline compared to relative small uphill. The velocity search space is therefore adjusted by the magnitude of the slope.

4. Simulation results

The choice of prediction and control horizons affects the performance of the MPC algorithm. Longer prediction horizons will generally give good results, but the downside is the longer computational time and inaccurate prediction due to eventual model errors and disturbances. The length of the control horizon decides how often the prediction/optimization procedure will be applied. The trade-off between computational complexity versus better performance is a balancing of factors all of which are not attainable at the same time. Moreover, the road environment for haulers is normally composed of frequent hills and it is hence necessary to test different horizon values in order to achieve satisfactory results.

Two sets of horizon values are tested and evaluated against the current gear shift strategy on a road section through computer simulation with Volvo CE's in-house software. This in-house simulation software includes complex dynamics of articulated haulers, and is regarded as highly accurate compared to the actual vehicles. The test road Måljord at Volvo CE's factory in Braås in Sweden, has steep uphill which resemble the haulers' normal working environment. In the first simulation, the horizon values are 80 and 65 discretization steps for the prediction and control horizons respectively, and the result are given in Figure 6. Simulations show that the proposed controller succeeds in reducing both fuel consumption and trip time with respectively 1.88% and 1.34%. The third subplot in Figure 6 shows that the MPC strategy shifted down earlier than the current strategy to gain more torque for the uphill, and MPC solution has less gear changes. Furthermore, the engine curve in the fourth subplot shows a smoother frequency.

Figure 7 shows the simulation results with prediction and control horizons of 20 and 10 steps respectively on the same road stretch. This solution gives simultaneous reductions of 3.11% in fuel use and 0.66% in travel time. We observe from the third plot in Figure 7 that the MPC controller generally chooses to shift gear before the current controller. The downshifts at 233 meter and 285 meter are prior to the current strategy to obtain the maximum torque to reduce the average speed loss before climbing a steep uphill. Though the speed of the vehicle drops at the beginning of the uphill (around 250 m in Figure 7), it is compensated by having a higher velocity after 300 meter so that the total travel time over the stretch is reduced. Upshifting at 423, 498 and 604 meter before downhill and a moderate uphill and letting the hauler accelerate by gravity is intuitive. The MPC controller also has fewer gear shifts to avoid waste of energy.

The behaviour of the MPC controller resembles what an experienced driver would do. However, the choices of discretization step, prediction/control horizon and the penalty parameters have strong influence on the control algorithm's behaviour. An in-depth examination of the MPC controller's behaviour with different parameter settings is still necessary.

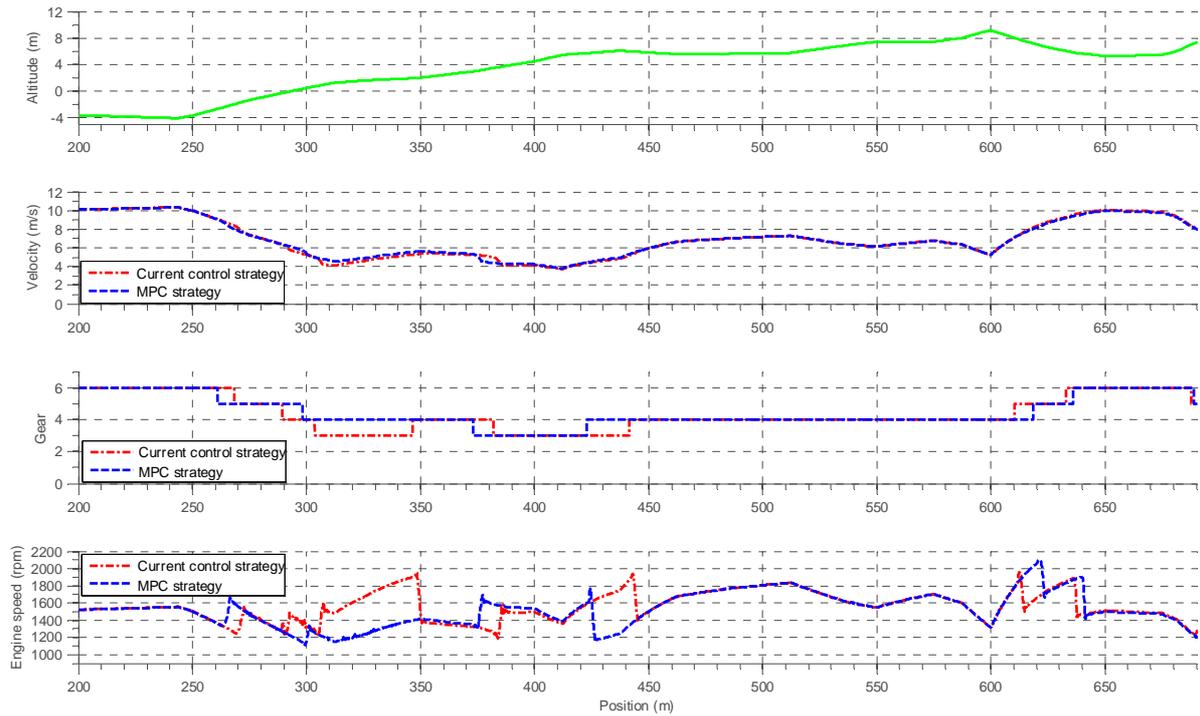


Figure 6. Simulation result on a road stretch of Målaåjord. The MPC strategy gives a fuel reduction of 1.88% and simultaneously a decrease in travel time of 1.34%.

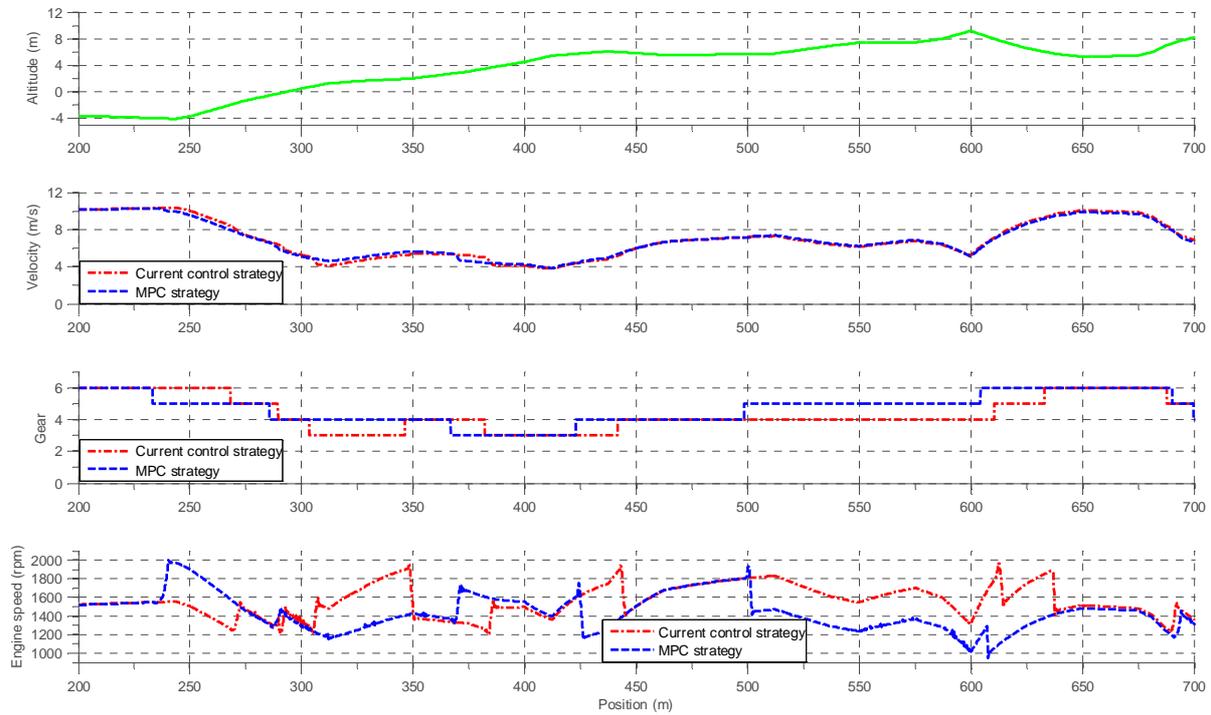


Figure 7. Simulation result with shorter prediction and control horizon. The MPC controller gives a fuel reduction of 3.11% and a decrease in trip time of 0.66%.

5. Conclusion

There are substantial potential gains in fuel economy for heavy construction vehicles by means of anticipating the driving environment. An optimal control problem is formulated to determine the optimal gear shift sequence for articulated haulers utilizing a GPS receiver and road topographical information. A model predictive control algorithm together with dynamic programming techniques are employed to solve the optimal gear shift problem.

Computer simulation shows that reductions of fuel consumption can be achieved using the proposed MPC algorithm. On a 500-meters road stretch, we obtain a decrease in fuel usage of 3.11% as compared to the current gear controller without increasing travel time. Prior to an uphill slope, the MPC algorithm chooses to shift down to accelerate so that the hauler will have a higher average velocity to climb the hill. In front of a downhill slope, the MPC shifts up to slow down the vehicle speed which is an intuitive way of saving fuel. The optimal gear shift sequence resembles the behaviour of an experienced driver.

This work is based on the assumption of available 3D maps of the driving environment for the construction equipment. In reality, it is rare that there are available topographical information for construction environments. Moreover, the environment at the construction sites is frequently re-configured due to the dynamic nature of construction operations. GPS devices have become standard equipment for construction vehicles in recent years. The measurements from GPS receivers and onboard sensors of vehicles could be utilized to estimate the road grade information (Sahlholm, 2001). This 3D map building method would provide road topographical information for the gear shift optimization algorithm.

Furthermore, the computational complexity of the MPC controller is yet to be further investigated to guarantee an efficient real-time implementation. We could perform off-line calculation or iterative optimization since the haulers often travel along the same path between a loading and dumping spot.

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