6th IFAC Symposium Advances in Automotive Control
Munich, Germany, July 12-14, 2010

# Switched Model Predictive Controller for Cruise Control of Heavy Trucks with Heuristic Trajectory Planning

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Abstract: **This paper introduces a model predictive control algorithm approach, which works as a cruise controller with automatic calculation of a speed level and trajectory. It aims on cost reduction for heavy trucks on long distance motorway operation compared with standard cruise controllers with driver adjusted speed level. It is assumed that the brake and the engine of the truck must be controlled by the predictive control algorithm but the robotized gear box does not need to be controlled. At this stage of development the approach is based on road topology information obtained through GPS positioning, 3D maps and a simplified linear model of the truck. It is assumed that there is no interaction with other traffic or the driver. The cruise control is split into a heuristic trajectory planning level and two real time capable MPCs. The heuristic module uses a simple nonlinear model of the truck and a slope map to calculate a limited horizon speed trajectory of the truck based on rules. The rules are acquired from driver training programs which approximate cost optimal driving. The lower level real time MPCs follow the trajectory considering the truck dynamic and the disturbance through slope profiles. Switching between engine and brake control is done by a switching logic. In contrast to other approaches we wanted to evaluate the cost saving potential with the simplest but therefore real time capable implementation on a standard automotive CPU like MPC5554. The approach considers only linearised models for unconstrained MPC but shows how to deal with limited control output. Also the switching problem between a MPC for the engine and a MPC for the brake will be described. A short comparison to other approaches regarding the saving potential, the real time capability and the robustness against parameter uncertainties are given**.

*Keywords:* Linear unconstrained MPC, truck, cruise control, heuristic, real time control

## 1. INTRODUCTION

From an economic as well as an ecologic point of view, the reduction of fuel consumption in truck traffic is considered as increasingly important. One way to address these issues is the extension of cruise control systems for trucks to model-based optimization of speed profiles such that topological route information is taken into account. Recently, a first few approaches were published that minimize fuel consumption based on optimization of dynamic models [1-10]. These approaches employ the principles of model predictive control (MPC) to optimize the speed trajectory according to the slope profile and to the characteristic parameters of the vehicle. These systems use GPS and 3D-maps to obtain information on the slope of the route, and a model of the vehicle to find a trajectory of control signals that minimizes a certain cost function. The main characteristics of such approaches are:

- The cost function reflects various parameters like fuel mass flow, deviation from demanded speed, soft constraints, etc.
- They apply numerical solvers because analytical solutions are infeasible with the nonlinear equations of the problem.
- The numerical solvers are often not efficient enough to produce the control trajectories in real time for the standard hardware of automotive control units.

In order to address in particular the goal of computing control strategies for reducing fuel consumption in real-time, this paper proposes an approach, in which a speed trajectory is first derived from heuristics using a nonlinear model and linear unconstrained model predictive controller are embedded to follow the speed trajectory.

## 2. TRUCK MODEL

The truck model used in this approach describes the dynamic of the truck, but skips a lot of essentials (e.g. fuel consumption map, nonlinear maximum torque table, internal friction, brake torque nonlinearities, variable time constant for engine turbo charger). There is one nonlinear model for engine operation and one for brake operation. It is assumed that there is no use case where both are required to be active at the same time. The engine model assumes a PT1 torque dynamic dependent on the accelerator pedal $u_e$ .

$$\dot{v} = \frac{i_{total}}{r_w \cdot m_{red}} M_{eng} - \frac{m \cdot g}{m_{red}}(\sin(\alpha) + \mu \cdot \cos(\alpha)) - \frac{c \cdot A \cdot \rho}{2 \cdot m_{red}} v^2$$

$$\dot{M}_{eng} = -\frac{1}{T_e} \cdot M_{eng} + \frac{K_{eng}}{T_e} \cdot u_e \quad (1+2)$$

The brake model assumes that the truck has a retarder brake system that can deliver any torque up to the maximum with a PT1 dynamic controlled by input $u_b$ :

$$\dot{v} = -\frac{i_{axis}}{r_w \cdot m_{red}} M_{br} - \frac{m \cdot g}{m_{red}}(\sin(\alpha) + \mu \cdot \cos(\alpha)) - \frac{c \cdot A \cdot \rho}{2 \cdot m_{red}} v^2$$

$$\dot{M}_{br} = -\frac{1}{T_{br}} \cdot M_{br} + \frac{K_{br}}{T_{br}} \cdot u_b$$

(3+4)

Both models have been linearised around a working point, transformed to a state space model and discretised in time. The inputs have been split in a controlled input and a disturbance input according to:

$$\hat{x}(k+1) = \hat{A} \cdot \hat{x}(k) + \hat{B}_{mu} \cdot \hat{u}(k) + \hat{B}_{mz} \cdot \hat{z}(k) \quad (5)$$

$$y = \hat{C} \cdot \hat{x}(k) \quad (6)$$

$\hat{u}(k)$ is the absolute brake or engine control signal around the working point and $\hat{z}(k)$ is the absolute slope around the working point. The later used MPC approach does not provide an integrator and the model doesn't have one too. Therefore it is necessary to extent the model with an integrator in order to avoid permanent deviation from desired working points. The approach can be found in [11]. First we switch to an incremental form:

$$\Delta x(k+1) = \hat{x}(k+1) - \hat{x}(k) \quad (7)$$

$$\Delta u(k) = \hat{u}(k) - \hat{u}(k-1) \quad (8)$$

$$\Delta z(k) = \hat{z}(k) - \hat{z}(k-1) \quad (9)$$

Than we introduce a new state: $x(k) = \begin{pmatrix} \Delta\hat{x}(k) \\ \hat{y}(k) \end{pmatrix}$

$$x(k+1) = \begin{pmatrix} \hat{A} & 0 \\ \hat{C} \cdot \hat{A} & 1 \end{pmatrix} x(k) + \begin{pmatrix} \hat{B}_{mu} \\ \hat{C} \cdot \hat{B}_{mu} \end{pmatrix} \Delta u(k) + \begin{pmatrix} \hat{B}_{mz} \\ \hat{C} \cdot \hat{B}_{mz} \end{pmatrix} \Delta z(k) \quad (10)$$

$$y(k) = (\,0\;0\;1\,)\; x(k)$$

This will be denoted as:

$$x(k+1) = A \cdot x(k) + B_u \cdot \Delta u(k) + B_z \cdot \Delta z(k) \quad (11)$$

$$y(k) = C \cdot x(k) \quad (12)$$

The model has been validated by experiments with a MAN TGX 19.440 truck. It shows sufficient quality if the model parameters are adapted to the driving situation $(c, \mu)$. Because this is a simulation we will use literature values and a non adaptive model in the following sections.

## 3. MPC CONTROLLER DESIGN

We use a classic MPC approach that can be found in [11] for the deviation of the MPC. We use the same controller structure for engine and brake control but with the according state space model for engine and brake. First we introduce a prediction horizon Np and control horizon Nc with Nc < Np. Then we take the final model from chapter 2 and write down the output for Np steps into the future and consider that $\Delta u(k)$ is 0 if the future output is more than Nc steps in the future we can write :

$$y(1) = C \cdot x(1) = C \cdot (\,A \cdot x(0) + B_u \cdot \Delta u(0) + B_z \cdot \Delta z(0)) \quad (13)$$

$$\vdots$$

$$y(i+1) = C \cdot \left[A^{i+1} \cdot x(0) + \sum_{h=Np-Nc}^{Np-1} (A^h \cdot B_u \cdot \Delta u(Np-h-1) + A^h \cdot B_z \Delta z(Np-h-1)\,)\right] \quad (14)$$

As a result we get :

$$\begin{bmatrix} y(1) \\ \vdots \\ y(n_p) \end{bmatrix} = S_x \cdot x(0) + S_u \cdot \begin{bmatrix} \Delta u(0) \\ \vdots \\ \Delta u(n_c-1) \end{bmatrix} + H_z \cdot \begin{bmatrix} z(0) \\ \vdots \\ z(n_p-1) \end{bmatrix} \quad (15)$$

with

$$S_x = \begin{bmatrix} C \cdot A \\ C \cdot A^2 \\ \vdots \\ C \cdot A^{n_p} \end{bmatrix} \quad (16)$$

$$S_u = \begin{bmatrix} C \cdot B_u & 0 & \cdots & 0 \\ C \cdot A \cdot B_u & C \cdot B_u & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ C \cdot A^{Np-1} \cdot B_u & C \cdot A^{Np-2} \cdot B_u & \cdots & C \cdot A^{Np-Nc} B_u \end{bmatrix} \quad (17)$$

$$H_z = \begin{bmatrix} C \cdot B_z & 0 & \cdots & 0 \\ C \cdot A \cdot B_z & C \cdot B_z & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ C \cdot A^{Np-1} \cdot B_z & C \cdot A^{Np-2} \cdot B_z & \cdots & C \cdot B_z \end{bmatrix} \quad (18)$$

The controller has the task to keep track of the trajectory but also to do this with moderate control action and control change. Therefore we decided to apply the classic cost function of MPC :

$$J = u^T \cdot W_u^2 \cdot u + \Delta u^T \cdot W_{\Delta u}^2 \cdot \Delta u + (y-r)^T \cdot W_y^2 \cdot (y-r) \quad (19)$$

Where u is the absolute control signal, $\Delta u$ is the incremental control signal, y is the predicted trajectory and r is the reference trajectory. The values of the weight matrices $W_u^2$, $W_{\Delta u}^2$ and $W_y^2$ have to be determined by experiment to fit the requirements of the controller design.

It is known that a long control horizon is useful but the numeric effort is high. On the other hand it is not necessary to change the control signal in each sampling step in order to have nearly the same control performance. Therefore we introduce the new control signal $w$ which depends on $\Delta u$ and u by the following relation :

$$\begin{bmatrix} \Delta u(0) \\ \vdots \\ \Delta u(n_c-1) \end{bmatrix} = J_w \cdot \begin{bmatrix} w(0) \\ \vdots \\ w(n_x-1) \end{bmatrix} \quad (20)$$

and

$$\begin{bmatrix} u(0) \\ \vdots \\ u(n_c-1) \end{bmatrix} = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 1 \end{bmatrix} J_w \cdot \begin{bmatrix} w(0) \\ \vdots \\ w(n_x-1) \end{bmatrix} \quad (21)$$

By choosing $J_w$ we are able to decide at any sampling step within the control horizon whether to allow a change in