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Optimization of Heavy Truck's Driveline Performance via Model Predictive Control rated by a Comfort Evaluation Algorithm

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Abstract: Finding the best compromise between comfort and dynamic during Tipin/out operations in heavy trucks is the aim of this project. Therefore, in this paper a new control concept is introduced based on model predictive control. The main parts of this concept are a fusion of the two different control targets comfort and dynamic to one resulting control variable and the design of a model predictive controller. This controller provides an optimal tracking of the predicted control target.
Due to the subjective perception of the driver, evaluating the comfort of a driving situation is not as easy as to describe the dynamic. Therefore, an online comfort evaluation algorithm based on objective measurement data is developed.
The very good performance of the developed control concept can be confirmed by this evaluation algorithm.

Keywords: systems with time-delays, optimal control theory, control problems under conflict and/or uncertainties, automobile powertrains, vehicle dynamic systems

1. INTRODUCTION

High dynamic driving behavior, which is similar to fast accelerations, is conflicted with comfortable driving experiences without driveline oscillations. However, solving this conflict has been considered for a long time. Especially in heavy trucks the impact of faster accelerations on the comfort of the vehicle is very distinct. Therefore, finding the best compromise between comfort and dynamic is indispensable for a good driving behavior.

Due to the aim to optimize the acceleration of a heavy truck, the driving operation of a Tipin and a Tipout is considered for further investigations.

An evaluation concept based on comfort and dynamic must be considered, due to be able to evaluate the behavior of the controlled vehicle. To benchmark the dynamic objective measurements like the acceleration of the vehicle can be considered. However, the evaluation of the comfort of the truck is dependent on the subjective perception of the passengers and not on objective data. Therefore, an online comfort evaluation algorithm must be developed to benchmark the results of the controlled systems.

Some controller concepts to find the best compromise have already been considered in this project.

A common solution of this problem is to limit the gradient of the engine torque as it can be seen in figure 1. However, although the dynamic of the vehicle is reduced the comfort is unacceptable. Regarding the oscillations in the driveline a ramp-shaped engine torque is not able to increase the comfort.

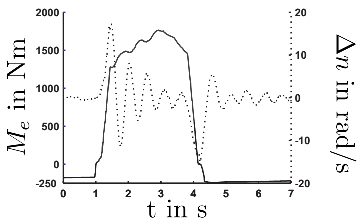

Fig. 1. A Tipin/out and its impact on the driveline; – engine torque, ··· difference of rotational speeds of engine and wheels

Therefore, in a first step an advanced PD-Controller was developed in (Webersinke, L. *et al.* 2007) to increase the comfort. The testing results show that the controller is able to minimize the oscillations in the driveline while the dynamic is of the same size as in the common solution. However, finding a compromise with a higher dynamic is not possible.

Therefore, a new concept based on state space controllers was developed in (Webersinke, Lena *et al.* 2008*a*). This concept includes two LQG-controllers, each of them supporting only comfort or dynamic behavior. By a fuzzy fusion with respect to the driving situation and the drive input the manipulated variables of both controllers are merged in a suitable manner. The resulting algorithm is able to compromise dynamic and comfort with focus on one of both targets. However, having two controllers, which work at the same time, can cause a conflict during a switching phase. Additionally, the parametrization of the algorithm to follow the desired compromise is difficult and the results of the controllers are not optimal.

Therefore, in this paper a new controller concept is introduced, which allows an optimal tracking of the control target as well as an easy way of parametrization. This concept is based on a simple driveline model which is described in section 2. Due to the optimal tracking, the implemented controller is based on the theory of model predictive control (MPC) (see section 3). However, finding the best compromise between comfort and dynamic with an easy way of parametrization was not possible in the former concepts. Therefore, an optimal control target is predicted based on the fusion of both conflicted goals. The calculation of this target is introduced in section 4. A first evaluation of the simulation results is discussed in section 5. However, describing the comfort behavior by objective measurements is not possible. Therefore, in section 6 the online comfort evaluation algorithm is introduced. After setting up a comfort model an implementation with the help of neuronal net work theory is described in section 7. Section 8 evaluates the comfort of the results of the controller concept based on the evaluation algorithm. The paper is summarized with a conclusion.

2. DRIVELINE MODEL

2.1 Drive-Shaft Model

Every MPC uses an explicit model of the process considered. Here, with respect to computing time as well as reproduction of the system's dynamic, a simple linear state-space model of 3rd order, the so-called drive-shaft model, is chosen (see (Kiencke, Uwe and Nielsen, Lars 2005)).

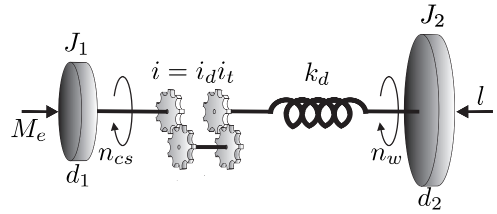

Fig. 2. The drive-shaft model

Therefore, the driveline is assumed to consist of two rotating inertias connected via a spring-damper element as shown in figure 2. The left inertia J_1 combines the engine, the clutch, the transmission (with ratio i) and the propeller shaft. The spring-damper element, described through its damping coefficient d_d and its stiffness k_d, represents the drive shaft. The second inertia J_2 models the wheels. The viscous friction of the two rotational inertias is taken into account through the damping coefficients d_1 and d_2, respectively.

J_1 is affected by the engine torque M_e and J_2 by the load l consisting of air drag, rolling resistance, and vehicle mass. Neglecting the engine friction, the engine torque M_e is the sum of the driver torque $M_d = u_d$ and the controller torque $M_c = u_c$.

Based on the drive-shaft model, a linear 3rd order state-space model can be derived by using Newton's generalized second law.

Defining the state vector $\underline{x}$ and the input vector $\underline{u}_{ext}$ to be

$$\underline{x} = \begin{bmatrix} \Delta\alpha \\ n_e \\ n_w \end{bmatrix}, \quad \underline{u}_{ext} = \begin{bmatrix} u_d \\ l \end{bmatrix}, \tag{1}$$

where n_e and n_w are the rotational speeds of the engine and the wheels, respectively, and $\Delta\alpha$ is the torsion between these two components, leads to

$$\dot{\underline{x}}(t) = \underline{A}\ \underline{x}(t) + \underline{b}_c\ u_c(t) + \underline{B}_{ext}\ \underline{u}_{ext} \tag{2}$$

$$\underline{y}(t) = \underline{C}\ \underline{x}(t) \tag{3}$$

where

$$\underline{A} = \begin{bmatrix} 0 & \frac{1}{i} & -1 \\ -\frac{k_d}{iJ_1} & \frac{-(d_1 + \frac{d_d}{i^2})}{J_1} & \frac{d_d}{iJ_1} \\ \frac{k_d}{J_2} & \frac{d_d}{iJ_2} & \frac{-(d_d + d_2)}{J_2} \end{bmatrix}, \tag{4}$$

$$\underline{b}_c = \begin{bmatrix} 0 \\ \frac{1}{J_1} \\ 0 \end{bmatrix}, \underline{B}_{ext} = \begin{bmatrix} 0 & 0 \\ \frac{1}{J_1} & 0 \\ 0 & -\frac{1}{J_2} \end{bmatrix}, \underline{C} = [\ 0\ \ 1\ \ (-i)\ ] \tag{5}$$

The controller can only influence u_c but not $\underline{u}_{ext}$.

For every gear the unknown parameters of this time-continuous model are estimated by using measured data and an appropriate identification algorithm (Webersinke, Lena *et al.* 2008*b*). For the MPC algorithm a time-discrete model is required and the Tustin approximation results in

$$\underline{x}(k+1) = \underline{A}_{dis}\underline{x}(k) + \underline{b}_{c,dis}u_c(k) + \underline{B}_{ext,dis}\underline{u}_{ext}(k) \tag{6}$$

$$\underline{y}(k) = \underline{C}\ \underline{x}(k). \tag{7}$$

2.2 Drive-Shaft Model with Time Delay

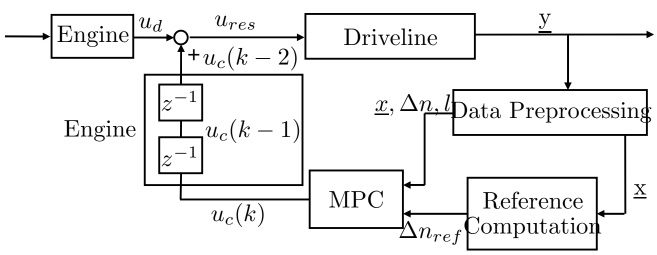

Fig. 3. Block diagram of the closed-loop system

The drive-shaft model is used by the MPC. However, there is an additional dead-time not considered yet. Figure 3 shows a block diagram of the closed-loop control. In simulation, u_d is measured at the output of the engine, whereas u_c still has to be processed by the engine. This results in a delay of approximately two sample times between the two signals. Due to the prediction of the MPC, this time delay can be considered.

Therefore, the state vector of the drive-shaft model is extended to

$$\underline{x}_{td}(k) = \begin{bmatrix} \Delta\alpha \\ n_e \\ n_w \\ u_c(k-1) \\ u_c(k-2) \end{bmatrix} \tag{8}$$

and the discrete state-space representation is of the form

$$\underline{x}_{td}(k+1) = \underline{A}_{td}\underline{x}_{td}(k) + \underline{b}_{c,td}u_c(k) + \underline{B}_{ext,td}\underline{u}_{ext,td} \tag{9}$$

$$\underline{y}(k) = \underline{C}_{td}\underline{x}_{td}(k) \tag{10}$$

with

$$\underline{A}_{td} = \begin{bmatrix} & & & 0 & \\ \underline{A}_{dis} & & & 0 & \underline{b}_{c,dis} \\ & & & 0 & \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \; \underline{b}_{c,td} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \tag{11}$$

$$\underline{B}_{ext,td} = \begin{bmatrix} \underline{B}_{ext,dis} & \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \; \underline{C}_{td} = [\, \underline{C} \;\; 0 \;\; 0 \,] \tag{12}$$

A MPC is designed using the drive-shaft model with and without time delay and the results are compared.

3. THEORY OF MPC

In the MPC algorithm, the system's behavior is predicted over a certain period of time, the prediction horizon p, at every sample time k. Using equations (6) and (7) the output of the system is predicted for the sample time $(k+i)$ to be

$$y((k+i)|k) = \Delta n((k+i)|k) = \underline{C}\left[\underline{A}_{dis}^{i}\,\underline{x}(k) + \sum_{h=0}^{i-1}\left(\underline{A}_{dis}^{(i-1)} \cdot \left(\underline{b}_{u_c}\left(u_c(k-1) + \sum_{j=0}^{h}\Delta u_c(j)\right) + \underline{B}_{ext}\underline{u}_{ext}\right)\right)\right]. \tag{13}$$

The cost function to be optimized is

$$J = \sum_{i=0}^{p-1}\left(\left|w_{i+1,j}^{\Delta n}\,(\Delta n(k+i+1|k) - r(k+i+1))\right|^2 + |w_i^{u_c}u_c(k+i|i)|^2\right) \tag{14}$$

$w_{i+1,j}^{\Delta n}$ and $w_i^{u_c}$ are the weights of the cost function and thus, the adjustable parameters of the MPC. r is the reference trajectory defining the target of the output variable Δn (see section 4).

Additionally, constraints of the form

$$u_{min} \le u \le u_{max}, \; y_{min} \le y \le y_{max} \tag{15}$$

are set up to take the system's constraints into account.

This results in a Quadratic Programming Problem which is to be solved. In order to obtain an optimal sequence

$$\underline{u}_{opt} = [u_{opt}(k)\; u_{opt}(k+1)\ldots u_{opt}(k+p)] \tag{16}$$

the Active Set Method ((Camacho, E.F. and Bordons, C. 2004)) is used and the first value $u_c(k) = u_{opt}(k)$ of this vector is passed through as manipulated variable.

Considering the principle of receding horizon, the algorithm is carried out at every sample time anew.

4. CALCULATION OF TARGET

In figure 1 Δn is shown during a Tipin/out operation without feedback control of the torque. Due to the driveline oscillation, driving comfort is poor. Δn is not only an indicator for comfort but also for dynamic. The higher the amplitude of the first oscillation after a Tipin/out the higher the dynamic but the less the comfort. The decrease of Δn after the first maximum also has a great influence on comfort. Last but not least, strong and long-lasting oscillations are perceived as jerking by the driver and cause a reduced comfort.

Hence, with respect to the control targets, a reference trajectory $r = \Delta n_{ref}$ with amplitude Δn_0 (see figure 4) is defined for Δn to reduce the oscillations and keep the maximal jerk under a certain limit.

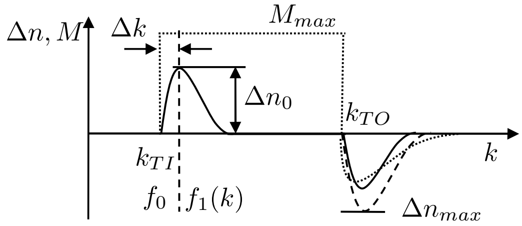

Fig. 4. Reference trajectory Δn_{ref} with parameters; $\cdots$ u_d

Adjusting the following parameters comfort and dynamic can be influenced. f_0 is the frequency at the start of the Tipin/out and

$$f_1(k) = \frac{f_0}{m(k)} = \frac{f_0}{m \cdot (k - k_{TI})} \tag{17}$$

is the frequency after Δn_{ref} has reached Δn_0. $m(k)$ is the decrease in frequency after Δn_0.

Δn_0 is not a parameter that can be set but is dependent on the driver's torque M_d. The maximum absolute value M_{max} of M_d is determined at the start of every Tipin/out operation. Assuming an approximately constant frequency of the oscillations, $\Delta n_{predict} = \Delta n(k + \Delta k|k)$ is predicted applying equation 13. Δk is the number of sample steps between the start of the Tipin/out operation and the first maximum of the oscillation of Δn.

However, to guarantee acceptable comfort, Δn_0 must not be larger than Δn_{max}.

$$\Delta n_0 = \begin{cases} \Delta n_{predict} & \text{if } \Delta n_{predict} \le \Delta n_{max} \\ \Delta n_{max} & \text{else} \end{cases} \tag{18}$$

Using this bounded amplitude Δn_0 the reference trajectory for a Tipin operation is

$$\Delta n_{ref} = \begin{cases} \Delta n_0 \cdot \sin \overbrace{(2\pi f_0\,(k - k_{TI}))}^{\Theta} \\ \qquad\qquad \text{if } TI \text{ and } (\Theta \le \frac{\pi}{2}) \\ \Delta n_0 \cdot \sin\left(2\pi f_1(k)\left(k - k_{TI} + \frac{(m(k)-1)}{4\,f_0}\right)\right) \\ \qquad\qquad \text{if } TI \text{ and } (\Theta > \frac{\pi}{2}) \end{cases} \tag{19}$$

In analogy, Δn_{ref} for the Tipout operation is computed. In Figure 4 the influence of the parameters on the reference is illustrated for the Tipout operation.

The reference trajectory combines the two targets high dynamic and high comfort and can be parameterized easily. The simulation results of a MPC using this reference are presented in the next section.

5. SIMULATION RESULTS

In order to demonstrate the good performance of the MPC, it is tested in simulation examining various parametrizations of the controller and of the algorithm computing the reference trajectory. Therefore, two different MPCs are implemented. One using the drive-shaft model which neglects the time delay (MPC1) and the other one which considers the time delay (MPC2). The results are compared. The systems works with a sample time of $T = 0.01$s. The prediction horizon is set to be 15.

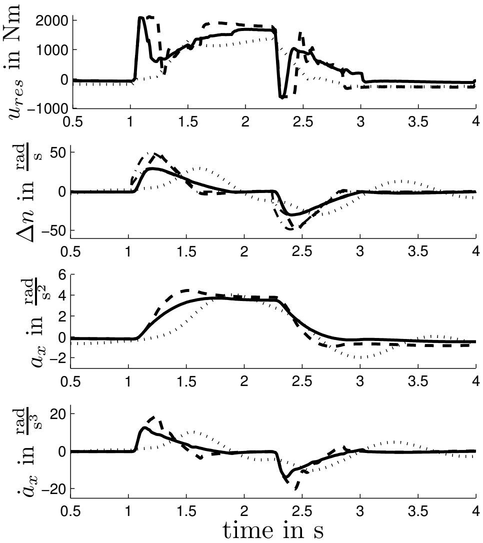

Fig. 5. Simulation results of MPC1 in gear 2; − high comfort, − − high dynamic, $\cdot - \cdot$ Δn_{ref}, $\cdots$ common solution

The weights of the MPC determine whether the emphasis of the control is on Δn to follow Δn_{ref} or u_{res} to become 0. The latter corresponds to a restricted controller intervention. Thus, the torque is expected to follow u_d. This can be achieved easily without any control action. As this section is supposed to illustrate the performance of the controller, the weights $w_{i,1}^{\Delta n}$ $(i = 1 \dots p)$ of Δn are chosen relatively large.

The main target of the controller is to find a good compromise between comfort and dynamic during a Tipin/out operation. Figure 5 shows an adjustment of the parameters for high comfort and one for high dynamic.

The main difference with respect to the parameters is in Δn_{max}. $\Delta n_{max} = 50$rad/s allows a higher dynamic than $\Delta n_{max} = 30$rad/s. Furthermore, the decrease in the frequency $f_1(k)$ is higher for the comfortable setting than for the dynamical one. However, even the comfortable setting of the parameters improves the dynamic and vice versa.

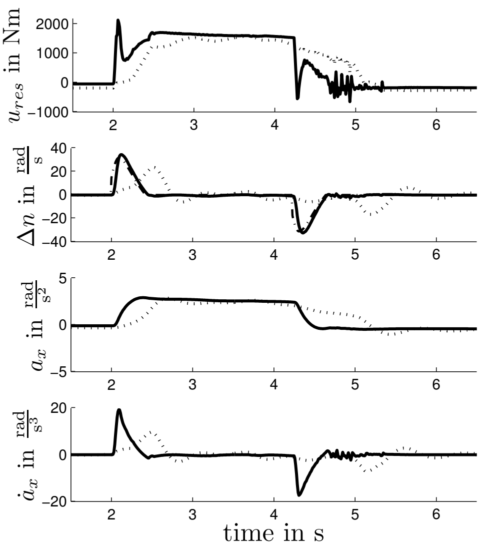

Fig. 6. Simulation results of MPC2 in gear 4; - MPC2, $\cdots$ common solution, $\cdot - \cdot$ Δn_{ref}

Due to the different number of states of the models implemented in MPC1 and MPC2 it is difficult to compare the performance of these two controllers directly. One set of parameters cannot be used for both controllers.
Figure 6 shows the simulation result for MPC2 in gear 4. The parameters are aiming for a high dynamic. Furthermore, the oscillations are reduced. Hence dynamic and comfort are increased.

MPC2 permits a higher intervention of the controller in the system's behavior. Furthermore, there are less oscillations than using MPC1.

In previous control strategies the performance of the controller was only satisfying for low gears. However, the simulation results in figure 6 demonstrate, that the MPC produces constantly good performance, even for higher gears.

Although Δn is used to control dynamic and comfort, it is only an indicator for comfort and dynamic. Due to evaluate the controller's performance with respect to comfort and dynamic an appropriate algorithm has to be defined. The dynamic of the controlled system can be rated easily by evaluating the acceleration a_x of the truck. However, the evaluation of the comfort is more complex. Therefore, an online algorithm for comfort evaluation is derived in the next section.

6. ALGORITHM FOR COMFORT EVALUATION

In literature a lot of work can be found concerning the evaluation of driving comfort in passenger cars (see (Gebert 2000)), but hardly anything concerning the driving comfort in trucks. Because of the truck's suspension these two kinds of vehicle cannot be treated the same way. Thus, an online algorithm for evaluation of the driving comfort in heavy trucks during Tipin/out operations is presented in this section.

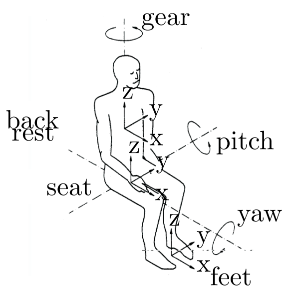

Fig. 7. Coordinate system to describe human perception of acceleration and jerk in different directions

Δn is a reasonable indicator for the driving comfort but it does not allow a reliable, objective evaluation due to the vehicle's suspension and the subjective impression of the driver.

Hence, an online comfort evaluation algorithm is implemented using the accelerations of the different directions of motion measured at the driver's cabin (see figure 7). In (Int 1997) filters are defined to model human's perception of oscillations. Generally, the vehicle occupant perceives oscillations of the frequency interval from approximately 1 Hz to 10 Hz most.

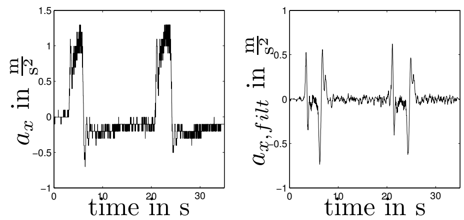

Fig. 8. a_x of driver cabin measured (left) and filtered with filter according to (Int 1997)(right)

Figure 8 illustrates the difference between the actual measured acceleration at the driver's cabin a_x and the filtered acceleration $a_{x,filt}$ perceived by the driver.

In order to obtain an objective comfort evaluation the filtered accelerations of four different directions of motion (x, z, pitch and roll) and the jerk $\dot{a}_x(t)$ are used to define characteristics c_i $(i = 1 \dots n)$. The higher a characteristic the worse the comfort. Therefore, features of the signals are considered like e.g. its energy or the amplitude of the oscillations. As an example, one of the characteristics is presented. The evaluation of the height of the edges running in opposite direction of $a_{x,filt}$ are evaluated after every Tipin/out operation. That is every section where $(\dot{a}_{x,filt} < 0)$ or $(\dot{a}_{x,filt} > 0)$ for a Tipin or Tipout, respectively. In order to obtain this characteristic the weighted sum is computed

$$c_1 = \frac{1}{N}\sum_{j=1}^{M}\left[w_{c1}(t)\cdot\left(\max_{\dot{a}_{x,filt}<0}(a_{x,filt}) - \min_{\dot{a}_{x,filt}<0}(a_{x,filt})\right)_j\right].$$

N is the total duration of the edges in opposite direction and M is their number. The weight $w_{c1}(t)$ is increasing with time. Similarly, the other characteristics are defined.

These parameters are summarized in one comfort characteristic value C that can be interpreted according to table 1. Hence, C can be computed online for every Tipin/out operation.

C	$0 \dots 1.5$	$3.5 \dots 4.5$	≥ 5.5
Interpretation	very good	acceptable	insufficient

Table 1. Interpretation of the comfort evaluation value C

However, before this comfort evaluation can be applied, the unknown function C has to be estimated. Therefore, a neural network is applied.

7. NEURAL NETWORK

A neural network is considered, due to the aim to approximate human feelings. This neural network is able to approximate unknown nonlinear functions depending on the inputs of the net. For further details to neural networks see (Brause, Rüdiger 1995).

Describing the comfort of a heavy truck the characteristics c_i are processed in two hidden layers and one output layer and results in a positive mark. However, the weights of each interconnection in this network must be adjusted. Therefore, the subjective feeling of drivers during Tipin/out operations expressed in marks on a scale from one to six (one - very good, six - very bad) was recorded. The corresponding characteristics c_i could be calculated out of the measured data of the CAN-bus. Hence, a training set existing of the net inputs c_i and the net output (subjective mark) is available. The neural network is trained with this set via backpropagation algorithm. The cost function of the quadratic error between the calculated net output and the target marks is minimized by an optimization algorithm based on the gradient method.

Due to get reasonable results a lot of test data of different drivers is necessary. However, every driver has a different notion of a comfortable behavior. Additionally, some subjective marks could be incorrect as the driver has to make his decision very fast. The net should be trained to the correct tendency and not to the absolut correct values, due to get an average comfort mark. Therefore, the training of the net must be stopped before the cost function is too small.

8. COMFORT EVALUATION OF MPC

For validation of the performance of the MPC two objectives must be considered: the comfort and the dynamic. The comfort can be described by the algorithm for comfort evaluation as described in chapter 6. The time difference to reach a change in the acceleration in the direction of motion of $1\frac{\text{rad}}{\text{s}^2}$ is used to evaluate the dynamic. Based on these evaluation algorithms the MPC was tested and compared with the former LQG-concept and the common solution introduced in section 1.

The following figures 9 and 10 show the results of a simulation with integrated calculation of the needed characteristics (e.g. pitch) for the comfort evaluation. The solid line represents the MPC and the dotted line the

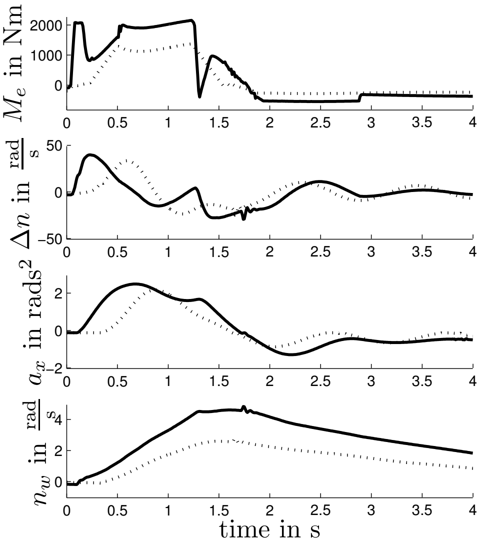

Fig. 9. The results for gear 2: $\cdots$ common solution, $--$ MPC

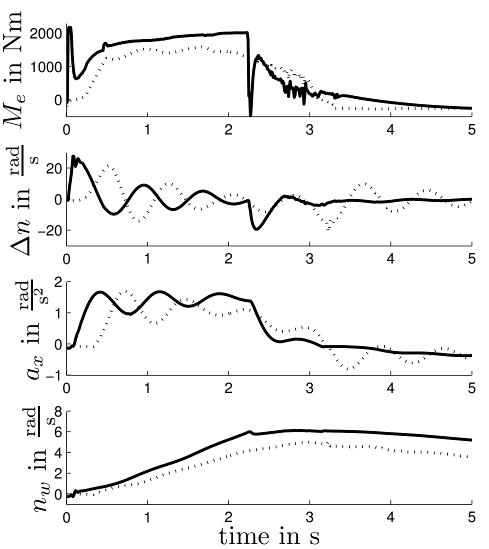

Fig. 10. The results for gear 4: $\cdots$ common solution, $--$ MPC

common solution (CS). Both considered adjustments of the predictive controller lead to nearly the same comfort as in the common solution, due to get comparable driving situations. Hence, the oscillation in the difference of rotational speeds is nearly the same for both systems. The results of validation of both objectives comfort and dynamic are summarized in table 2. The evaluation for lower gears represented by gear 2 (figure 9) and for higher ones represented by gear 4 (figure 10) will be discussed in the following.

However, although the comfort is nearly the same the dynamic according to the characteristic of the lateral acceleration a_x is enhanced by the MPC. The considered time for acceleration is reduced by 50% for a Tipin in gear 2 and by nearly 85% in gear 4. The former LQG-

	gear	TI comf	TI dyn	TO comf	TO dyn
CS	2	3.2	0.6	2.8	0.4
MPC	2	2.9	0.3	2.5	0.3
CS	4	4.3	1.3	1.3	1.7
MPC	4	4.3	0.2	1.5	0.3

Table 2. The evaluation. CS: common solution, TI: Tipin, TO: Tipout

concept is not able to enhance the dynamic for higher gears as time delays and active constraints preponderate there. This large improvement by the MPC shows the very good performance of the presented algorithm.

9. CONCLUSION

The model predictive controller considering the time delay of the engine with combination of the control target calculation is able to increase the performance during acceleration phases very well. The easy way to parameterize this algorithm and the new definition of the control target enables a high dynamical and comfortable behavior of the heavy truck. Up to now it was not possible to increase the dynamic while the comfort remains acceptable for higher gears, too. Hence, using the described algorithm the dynamic can be increased up to 85% compared with the common solution.

A comfort validation of the different control concepts using the developed comfort evaluation algorithm helps to optimize the performance and to give significant evaluation results.

In future works an adaptive algorithm should be included into the model predictive concept to enhance the performance of the system and to adapt it to other driveline configurations.

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