Nonlinear Model Predictive Control of a Diesel Engine Airpath *

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Abstract: In this paper we show the Nonlinear Model Predictive Control (NMPC) of an airpath of a diesel engine based on a Linear Parameter Varying (LPV) model. We used databased LPV modelling with real data from a dynamical engine test bench in order to obtain a nonlinear model of high quality. Because of the nonlinearity of the model the quadratic program (QP) of the NMPC needs to be set up afresh at each sampling instant, which is the main difference to standard linear MPC. For solving the QP efficiently, we employ the recently developed online active set as implemented in the software package qpOASES. We tested our controller in simulation on the LPV model identified on a mean value model and results show that the NMPC has a better tracking performance in terms of boost pressure and fresh air mass flow compared to the standard linear MPC approach also under the influence of a model plant mismatch.

Keywords: Nonlinear Model Predictive Control, LPV Modelling, Diesel engine control, Online QP solution

1. INTRODUCTION

Nowadays Diesel engines are equipped with an Exhaust Gas Recirculation (EGR) valve and Variable Geometry Turbine (VGT) turbocharger in order to cope with the emissions restrictions and drivability requirements. In a standard Engine Control Unit (ECU) the EGR valve controls the desired Mass Air Flow (MAF) through the compressor and the VGT controls a desired boost pressure, also called Manifold Absolute Pressure (MAP). This is usually performed with two SISO control loops almost ignoring the fact that the airpath is a coupled MIMO system.

Airpath control has been a wide research area in the last years. MIMO control approaches are presented e.g. in (Jankovich (2000), Utkin et al (2000), Niewstadt (1998), Ammann (2003)).

Recent results (Ortner (2007)) have shown that there is a lot of potential in the MIMO control of the EGR valve and the VGT when using predictive control algorithms able to cope with the existing actuator constraints. In a former work (Ortner (2007)) we used databased multilinear models in order to apply explicit model predicitve control algorithms (Bemporad (2002)) on a real production car engine, which already lead to an impressive improvement in terms of MAF and MAP tracking, and we also showed that emissions can be lowered. The latter works only if additionally to the controller also the setpoints for MAF and MAP are changed. In this work we want to model the airpath with a Linear Parameter Varying (LPV) model instead of the multilinear approach. This should lead to a superior tracking result since switching in the controller is avoided.

Similar to (Wei (2007)) we use a databased LPV approach to identify a nonlinear model for control. It is based on a least squares minimization similar to linear identification techniques, like ARX (Ljung (1999)), but able to incorporate a scheduling parameter ρ which has to be chosen appropriate. In contrary to (Wei (2007)) we have chosen a different model structure consisting of two MISO models, one for MAF and one for MAP, which turned out to work best on the Diesel engine airpath we identified. For controlling the airpath we use a Nonlinear Model Predictive Controller (NMPC). The main difference to a standard linear MPC is that the Quadratic Program (QP) needs to be condensed each sampling instant since the model parameters depend nonlinearly on the actual state. We use a stand alone version to solve the QP instead of solving a sequential QP which would require much more computing power. Our QP solver is based on an online active set strategy introduced and testet in (Ferreau (2007)). Simulation results show that the NMPC controller can cope much better with the nonlinearities than a linear MPC can. To test the robustness of the NMPC controller we show simulations on a mean value engine model (Langthaler (2007)) where a model plant mismatch occurs. Again the NMPC shows superior tracking results than a linear MPC does.

This paper is organized as follows. In Section 2 we introduce the identification algorithm for databased LPV mod-

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elling, Section 3 shows the application of this algorithm to the airpath structure. Section 4 will explain the nonlinear model predictive controller in general and Section 5 will explain the NMPC for the airpath model. In Section 6 we will compare the NMPC controller against a linear MPC and finally Section 7 will conclude.

2. DATABASED LPV MODELLING

We will shortly introduce the method of identifying the parameters of a LPV model. Similar to linear system identification (Ljung (1999)) we fix the ARX (autoregression with exogenous input) case leading to the following error system

$$A\left(q^{-1},\rho_k\right)y\left(k\right)=B\left(q^{-1},\rho_k\right)u\left(k\right)+m_k \tag{1}$$

with $y\left(k\right)$, $u\left(k\right)$ and $m\left(k\right)$ the output, the input and the error in the actual sampling instant. ρ_k is the scheduling vector. The polynomials A and B have the form

$$\begin{array}{l} A\left(q^{-1},\rho_k\right)=1+a_1\left(\rho_k\right)q^{-1}+...+a_{n_a}\left(\rho_k\right)q^{-n_a} \\ B\left(q^{-1},\rho_k\right)=b_1\left(\rho_k\right)q^{-1}+...+b_{n_b}\left(\rho_k\right)q^{-n_b} \end{array} \tag{2}$$

We assume that the parameters of the polynomials A and B depend on the scheduling vector ρ in the following way

$$\begin{array}{l} a_i\left(\rho_k\right)=a_i^0+a_i^1f_1\left(\rho_k\right)+...+a_i^{N-1}f_{N-1}\left(\rho_k\right) \\ b_i\left(\rho_k\right)=b_i^0+b_i^1f_1\left(\rho_k\right)+...+b_i^{N-1}f_{N-1}\left(\rho_k\right) \end{array} \tag{3}$$

where the functions $f_1(\rho_k)...f_{N-1}(\rho_k)$ are design parameters. When combining equations (2) and (3) we get

$$\begin{array}{l} A\left(q^{-1},\rho_k\right)=1+\left(a_1^0q^{-1}+...+a_{n_a}^0q^{-n_a}\right) \\ +f_1\left(\rho_k\right)\left(a_1^1q^{-1}+...+a_{n_a}^1q^{-n_a}\right)+...+ \\ f_{N-1}\left(\rho_k\right)\left(a_1^{N-1}q^{-1}+...+a_{n_a}^{N-1}q^{-n_a}\right) \end{array} \tag{4}$$

$$\begin{array}{l} B\left(q^{-1},\rho_k\right)=\left(b_1^0q^{-1}+...+b_{n_b}^0q^{-n_b}\right) \\ +f_1\left(\rho_k\right)\left(b_1^1q^{-1}+...+b_{n_b}^1q^{-n_b}\right)+...+ \\ f_{N-1}\left(\rho_k\right)\left(b_1^{N-1}q^{-1}+...+b_{n_b}^{N-1}q^{-n_b}\right) \end{array}$$

Using the definitions

$$\begin{array}{l} \phi_k=\left[\,-y_{k-1}\;-y_{k-2}\;\cdots\;-y_{k-n_a}\;u_{k-1}\;u_{k-2}\;\cdots\;u_{k-n_b}\,\right] \\ \theta^i=\left[\,a_1^i\;a_2^i\;...\;a_{n_a}^i\;b_1^i\;b_2^i\;...\;b_{n_b}^i\,\right]^T \\ F_k=\left[\,1\;f_1\left(\rho_k\right)\;\cdots\;f_{N-1}\left(\rho_k\right)\,\right] \end{array} \tag{5}$$

we can rewrite equation (1) like

$$\begin{array}{l} y\left(k\right)=\phi_k\theta^0+f_1\phi_k\theta^1+...+f_{N-1}\phi_k\theta^{N-1}+m_k \\ =\left(\,\phi_k\;f_1\phi_k\;\cdots\;f_{N-1}\phi_k\,\right)\begin{pmatrix}\theta^0\\ \theta^1\\ ...\\ \theta^{N-1}\end{pmatrix}+m_k \\ =\left(F_k\otimes\phi_k\right)\Theta+m_k \\ =\Gamma_k\Theta+m_k \end{array} \tag{6}$$

with

$$\begin{array}{l} \Theta=\left[\,\left(\theta^0\right)^T\;\left(\theta^1\right)^T\;...\;\left(\theta^{N-1}\right)^T\,\right]^T \\ \Gamma_k=\left(F_k\otimes\phi_k\right) \end{array} \tag{7}$$

Using N_m measurements we can put equation (6) in the more generalized matrix form

$$Y=\Gamma\Theta+M \tag{8}$$

with

$$\begin{array}{l} Y=\left(\,y_1\;y_2\;\cdots\;y_{N_m}\,\right)^T \\ \Gamma=\left(\,\Gamma_1\;\Gamma_2\;...\;\Gamma_{N_m}\,\right)^T \end{array} \tag{9}$$

which leads to the least squares estimate for the parameter vector

$$\hat{\Theta}=\left(\Gamma^T\Gamma\right)^{-1}\Gamma^TY \tag{10}$$

which can be shown to converge to the real parameter vector under the assumption of white noise for m_k. Please refer to (Wei (2006)) for a more detailed identification algorithm.

3. LPV MODELLING OF THE AIRPATH

The structure of a Diesel engine airpath according to Figure 1 is mainly composed of the turbocharger, the EGR valve and the inlet and exhaust manifold. The fresh air is compressed and mixed with the already burnt gas which is fed back by the EGR valve and acts as an inert gas during the combustion. This is a necessary task in order to decrease the peak combustion temperature and therefore the formation of nitrous oxides. The exhaust gas drives the turbine which in turn drives the compressor via a common shaft. Since both the EGR path and the turbine are driven by the exhaust gas these two systems are strongly coupled. A common Electrical Control Unit (ECU) in a production car only considers this coupling in a feedforward part when controlling the fresh air through the compressor and the boost pressure.

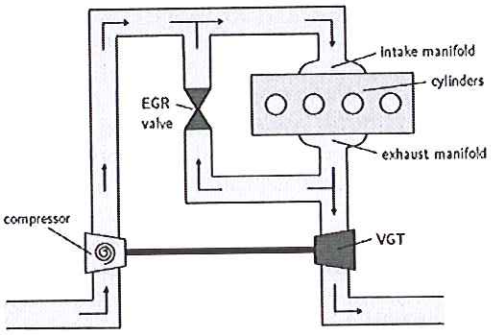


Fig. 1. Structure of a Diesel Engine Airpath

Jung (2003) showed how to simplify a higher order mean value model to obtain a LPV model. We decided to directly identify a LPV model in order to avoid the enormous parametrization work of a mean value model. In order to apply the LPV identification algorithm to the airpath system we used four parallel transfer functions for the modelling of MAF and MAP according to Figure 3 which shows the MAP part of our model. The model inputs are the EGR position, the VGT position, the engine speed N and the fuel flow m_f which turned out to be the most important variables for the airpath identification. EGR and VGT form the manipulated variables while N and m_f are the measured disturbances. The global model structure is depicted in Figure 2.

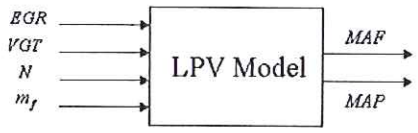


Fig. 2. Inputs and Outputs of LPV Model

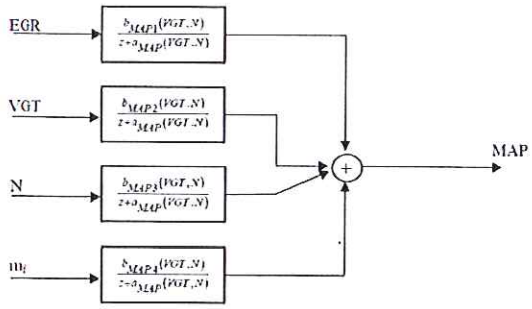


Fig. 3. Structure of the MAP Model

Each of the transfer functions has the same A polynomial but different B polynomials. The following assumptions for the transfer functios turned out to result in the best model quality.

$$G = \frac{b_1(\rho_k)\, q^{-1}}{1 + a_1(\rho_k)\, q^{-1}} \tag{11}$$

with the scheduling vector ρ_k equal to the VGT position and engine speed N

$$\begin{aligned} a_i(\rho_k) &= a_i^0 + a_i^1 VGT + a_i^2 N + a_i^3 VGTN \\ b_i(\rho_k) &= b_i^0 + b_i^1 VGT + b_i^2 N + b_i^3 VGTN \end{aligned} \tag{12}$$

For the excitation of the inputs EGR and VGT and the external disturbances N and m_f white noise signals with different sample times were used around a specified mean value which is shown in Figure 4. To avoid a damage of the engine, caused by too high manifold air pressures, the maximum VGT position was constrained at higher engine speeds. Also the mean value of the engine speed was changed every 150 seconds to reach the whole operating range.

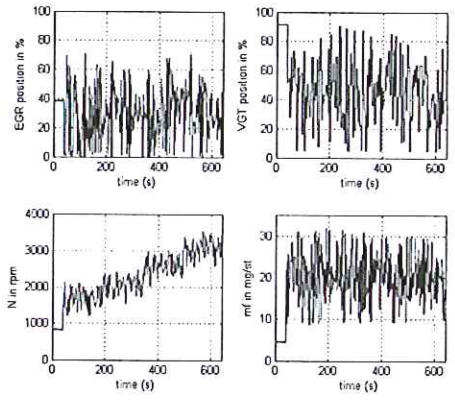


Fig. 4. Input Excitation for Airpath Identification

Figure 5 and 6 show the validation results of the LPV model evaluated on the dataset from a FTP75 driving cycle. This dataset was not included in the identification data. The main dynamics of MAF and MAP are well captured by the LPV model, which in turn allows to use it as prediction model in the NMPC.

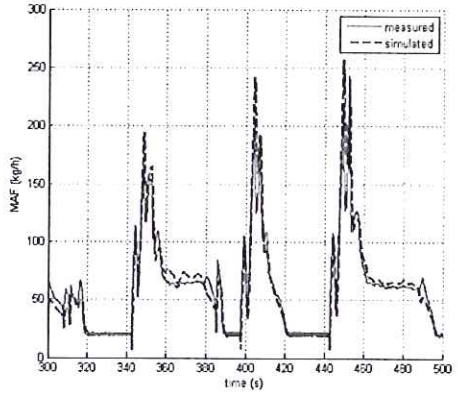


Fig. 5. Validation of MAF Model on FTP75 Driving Cycle

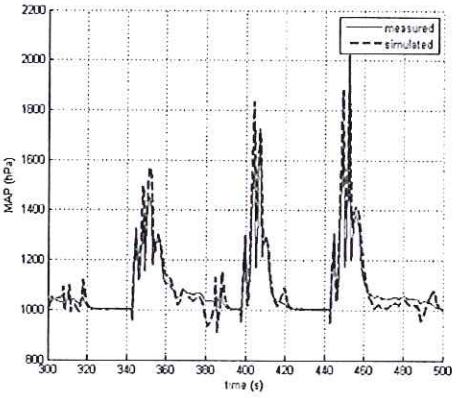


Fig. 6. Validation of MAP Model on FTP75 Driving Cycle

4. NMPC CONTROL

4.1 General MPC Concept

Our formulation of a tracking MPC control algorithm aims at ensuring that the model output y follows a desired reference trajectory y_{ref} (which can be interpreted as a generalization of system stabilization). The deviation from the reference is to be minimized over a specified time horizon in order to keep the plant output as close as possible to the desired output. To this end a cost function J is defined, which is chosen to be quadratic in most cases. At each sampling instant the result of the optimization is a sequence of input signals where only the first input is actually applied to the plant. This leads to a so-called receding horizon approach as shown in Figure (7).

4.2 LPV NMPC Control

We use a linear parameter-varying model and a convex-quadratic cost function leading to the following discrete-

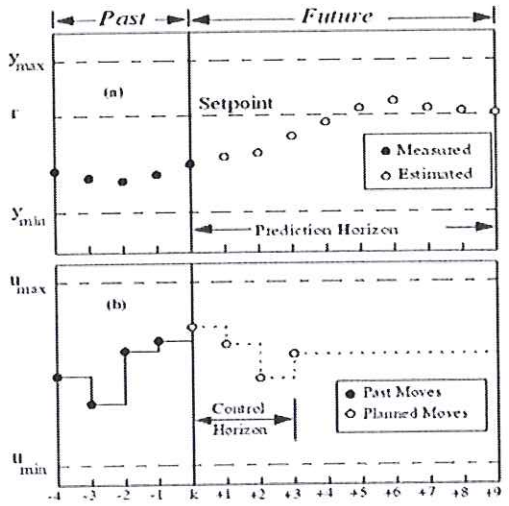


Fig. 7. MPC Tracking Problem

time optimal control problem to be solved at each sampling instant:

$$\begin{aligned} \min_{u} \; & \frac{1}{2}\sum_{k=0}^{N_{\mathrm{PH}}} (y_k - y_{\mathrm{ref}})^T Q (y_k - y_{\mathrm{ref}}) + u_k^T R u_k \\ \text{s. t} \quad & x_0 \text{ given} \\ & x_{k+1} = A_k x_k + B_k u_k + Z v \\ & y_k = C_k x_k \\ & \underline{x} \le x_k \le \bar{x} \qquad \forall k = 0 ... N_{\mathrm{PH}} \\ & \underline{u} \le u_k \le \bar{u} \qquad \forall k = 0 ... N_{\mathrm{CH}} - 1 \\ & u_k = 0 \qquad \forall k = N_{\mathrm{CH}} ... N_{\mathrm{PH}} \end{aligned} \tag{13}$$

Therein, v represents the measured disturbances which are assumed to be constant over the whole prediction horizon and N_{PH} and N_{CH} denote the so-called prediction and control horizon, respectively. Note that the matrices A_k, B_k and C_k vary along the prediction horizon as they depend nonlinearly on the current system state and the engine speed. They are obtained via an online integration starting from the current system state and applying the optimized inputs obtained at the last sampling instant. We can compute the states for the whole prediction horizon as follows (using a control horizon of three):

$$\begin{aligned} x_1 &= A_0 x_0 + B_0 u_0 + Z v \\ x_2 &= A_1 x_1 + B_1 u_1 + Z v \\ &= A_1 (A_0 x_0 + B_0 u_0) + B_1 u_1 + Z v \\ &= A_1 A_0 x_0 + A1 B_0 u_0 + B_1 u_1 + A_1 Z v + Z v \\ &\dots \\ x_{N_{\mathrm{PH}}} &= (A_{N_{\mathrm{PH}}-1} ... A_0) x_0 + (A_{N_{\mathrm{PH}}-1} ... A_1 B_0) u_0 + \\ &\quad (A_{N_{\mathrm{PH}}-1} ... A_2 B_1) u_1 + (A_{N_{\mathrm{PH}}-1} ... A_3 B_2) u_2 + \\ &\quad \dots + Z v \end{aligned} \tag{14}$$

By introducing matrices S_0 and S_1, the problem can be re-formulated in a straigth-forward manner as

$$\tilde{x} = \begin{pmatrix} S_0 & S_1 \end{pmatrix} \begin{pmatrix} x_0 \\ \tilde{u} \end{pmatrix} + \tilde{v}, \tag{15}$$

where $\tilde{x}$, $\tilde{u}$, and $\tilde{v}$ are the states, inputs and measured disturbances along the horizon stacked into a single vector, respectively.

Now substitute this into the MPC problem formulation (equation 13). For reasons of clarity, the dependency between the model outputs and the system states is assumed to be $y_i = x_i$; for the general case, only substitution $y_i = C_i x_i$ needs to be done. Hence, the QP formulation turns into

$$\begin{aligned} \min_{\tilde{u}} \; & \frac{1}{2} (\tilde{x}_i - \tilde{I} x_{\mathrm{ref}})^T \tilde{Q} (\tilde{x}_i - \tilde{I} x_{\mathrm{ref}}) + \tilde{u}_i^T \tilde{R} \tilde{u}_i \\ \text{s. t} \quad & x_0 \text{ given} \\ & \begin{pmatrix} \underline{x} \\ \dots \\ \underline{x} \end{pmatrix} \le \tilde{x} \le \begin{pmatrix} \bar{x} \\ \dots \\ \bar{x} \end{pmatrix} \\ & \begin{pmatrix} \underline{u} \\ \dots \\ \underline{u} \end{pmatrix} \le \tilde{u} \le \begin{pmatrix} \bar{u} \\ \dots \\ \bar{u} \end{pmatrix} \end{aligned} \tag{16}$$

where $\tilde{Q} = \mathrm{diag}(Q, Q, ..., Q)$, $\tilde{R} = \mathrm{diag}(R, R, ..., R)$, $\tilde{I} = (I, I, ..., I)^T$. By combining equation (15) and (16) and leaving the constant parts away, this leads to

$$\begin{aligned} \min_{\tilde{u}} \; & \frac{1}{2} \tilde{u}^T (S_1^T \tilde{Q} S_1 + \tilde{R}) \tilde{u} + \tilde{u}^T S_1^T (S_0 x_0 + \tilde{v} - \tilde{I} x_{\mathrm{ref}}) \\ \text{s. t} \quad & x_0 \text{ given} \\ & \begin{pmatrix} \underline{x} \\ \dots \\ \underline{x} \end{pmatrix} - S_0 x_0 - \tilde{v} \le S_1 \tilde{u} \le \begin{pmatrix} \bar{x} \\ \dots \\ \bar{x} \end{pmatrix} - S_0 x_0 - \tilde{v} \\ & \begin{pmatrix} \underline{u} \\ \dots \\ \underline{u} \end{pmatrix} \le \tilde{u} \le \begin{pmatrix} \bar{u} \\ \dots \\ \bar{u} \end{pmatrix} \end{aligned} \tag{17}$$

Finally, by summarising $w_0 = (x_0, v)$, this can be rewritten as a parametric quadratic problem of the form

$$\begin{aligned} \min_{\tilde{u}} \; & \frac{1}{2} \tilde{u}^T H \tilde{u} + \tilde{u}^T g(w_0) \\ \text{s. t} \quad & lb_G(w_0) \le G\tilde{u} \le ub_G(w_0) \\ & lb(w_0) \le \tilde{u} \le ub(w_0) \end{aligned} \tag{18}$$

which we are solving with an online active set strategy proposed and tested in (Ferreau (2007)). The implementation is based on the open-source software package qpOASES (qpOASES Homepage (2008)).

5. NMPC CONTROL OF AIRPATH MODEL

5.1 State Space Transformation

The LPV identification leads to a transfer function model of the airpath. For using it in NMPC, we transform it into a state-space description which results in the following model here shown only for MAF (MAP has exactly the same structure with different parameters labelled MAP instead of MAF).

$$x_{\mathrm{MAF}_{k+1}} = A_{\mathrm{MAF}} x_{\mathrm{MAF}_k} + B_{\mathrm{MAF}} * \begin{bmatrix} u_k \\ v_k \end{bmatrix}$$
$$y_{\mathrm{MAF}_k} = C_{\mathrm{MAF}} x_{\mathrm{MAF}_k}$$

$$A_{\mathrm{MAF}} = \begin{bmatrix} \alpha_1 & 0 & 0 & 0 \\ 0 & \alpha_1 & 0 & 0 \\ 0 & 0 & \alpha_1 & 0 \\ 0 & 0 & 0 & \alpha_1 \end{bmatrix} \quad \alpha_1 = a_{1_{\mathrm{MAF}}}(\rho_k) \tag{19}$$

$$B_{\mathrm{MAF}} = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} \quad u_k = \begin{bmatrix} EGR \\ VGT \end{bmatrix} \quad v_k = \begin{bmatrix} N \\ m_f \end{bmatrix}$$

$$C_{\mathrm{MAF}} = [\, b_{1_{\mathrm{MAF}}} \;\; b_{2_{\mathrm{MAF}}} \;\; b_{3_{\mathrm{MAF}}} \;\; b_{4_{\mathrm{MAF}}} \,]$$

where u_k is the vector of the manipulated variables and v_k contains the external disturbances. To incorporate constraints on the rate of change of the manipulated variables the whole model needs to be rewritten as

$$\begin{bmatrix} x_{k+1} \\ u_{k+1} \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ u_k \end{bmatrix} + \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} v_k \\ \Delta u_k \end{bmatrix}$$

$$y_k = [\, C \;\; 0 \,] \begin{bmatrix} x_k \\ u_k \end{bmatrix} \tag{20}$$

$$A = \begin{bmatrix} A_{\mathrm{MAF}} & 0 \\ 0 & A_{\mathrm{MAP}} \end{bmatrix} \quad B = \begin{bmatrix} B_{\mathrm{MAF}} \\ B_{\mathrm{MAP}} \end{bmatrix}$$

$$C = \begin{bmatrix} C_{\mathrm{MAF}} \\ C_{\mathrm{MAP}} \end{bmatrix} \quad x_k = \begin{bmatrix} x_{\mathrm{MAF}_k} \\ x_{\mathrm{MAP}_k} \end{bmatrix}$$

and additionally an output disturbance model has to be added in order to account for modelling uncertainties. We used a simple integrator driven by white noise as our output disturbance model leading to

$$\begin{bmatrix} x_{k+1} \\ u_{k+1} \\ e_{k+1} \end{bmatrix} = \begin{bmatrix} A & B & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ u_k \\ e_k \end{bmatrix} + \begin{bmatrix} I & 0 \\ 0 & I \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_k \\ \Delta u_k \end{bmatrix}$$

$$y_k = [\, C \;\; 0 \;\; I \,] \begin{bmatrix} x_k \\ u_k \\ e_k \end{bmatrix} \tag{21}$$

which is finally used as the prediction model in the nonlinear controller.

5.2 Input Constraints and Control Horizons

In the Diesel engine airpath the two control inputs EGR and VGT are limited to positions between 0% and 100%. Also the rate of change for these actuators is restricted. Another physical boundary of the airpath is the maximum manifold absolute pressure. The MAP is basically caused by the rotation speed of the engine and the position of the VGT guide vanes and could damage the airpath's manifold or the turbocharger itself. Therefore the maximum valid VGT position additionally decreases for higher engine speeds.

We have chosen the prediction horizon $N_{\mathrm{PH}} = 120$ which is a period of time of 6 sec (Sampling Time: 50 ms). This possibly large seeming interval is necessary to evaluate the model correctly since in some points it turns out to be non minimum phase. We fixed the control horizon $N_{\mathrm{CH}} = 3$ which results in a very good tracking performance.

5.3 Observer Design

The QP (equation 18) which needs to be solved each sampling instant depends on the actual state of the plant. Therefore it is necessary to estimate the state via an observer. We have chosen to use an Extended Kalman Filter (EKF) which can be easily tuned and it turned out to work well. The model for the observer is the same as the prediction model (equation (21)) but without the Δu formulation, which is not necessary for the observer design. Also the measured disturbances v can be considered in the standard input vector.

6. SIMULATION RESULTS

In order to test the LPV NMPC against a standard linear MPC we linearized our identified LPV model and designed a linear MPC with the same cost function weights Q and R as the nonlinear. Figure 8 shows the simulation tracking results of freely chosen setpoints for MAF and MAP and Figure 9 shows the according actuator signals. As expected the NMPC performs better since it incorporates the exact model. In the time from 100sec to 130sec where the setpoint is near to the linearization point we see a similar behavior but getting away from the linearization point leads to overshoots in the linear MPC.

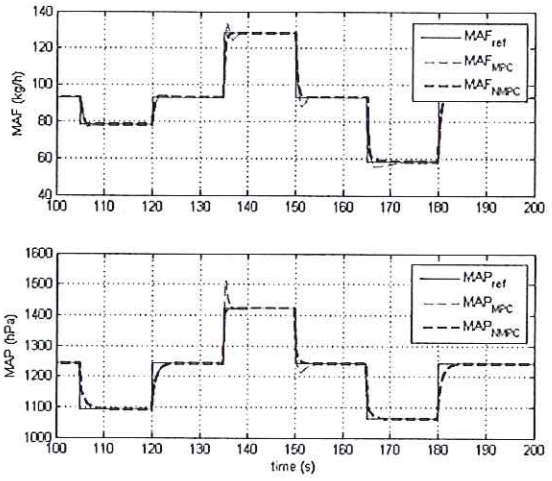


Fig. 8. MAF/MAP Tracking on LPV Model

In order to cope with a model plant mismatch we also tested the LPV NMPC controller on a mean value model presented in Langthaler (2007). We identified a LPV model and a linear model in simulation and again compared the two controllers leading to the results which can be seen in Figure 10 and the actuator signals in Figure 11, showing again a clear advantage of the nonlinear controller against the linear. Although the experiments where performed only in a small operating area, where one could think of a linearizing controller to perform satisfactory we still see a clear advantage of the nonlinear controller.

7. CONCLUSION

In this work we have developed a MIMO airpath control of a Diesel engine by means of databased LPV modelling

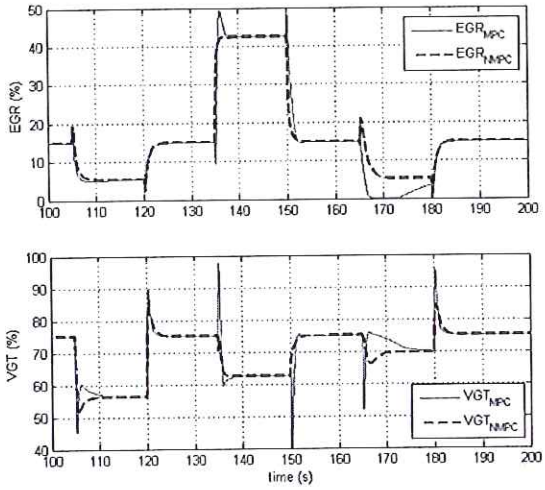


Fig. 9. Control Signals for Tracking on LPV Model

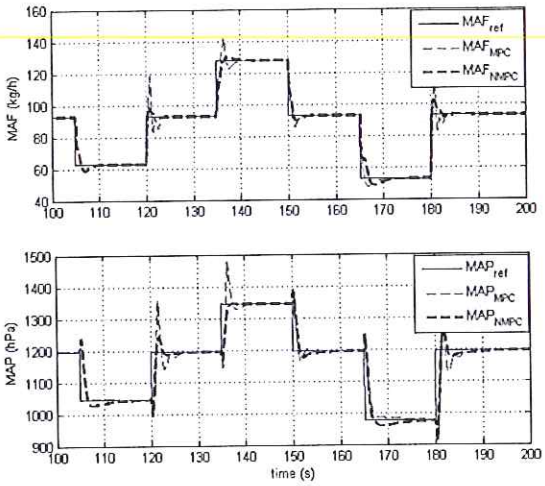


Fig. 10. MAF/MAP Tracking on MVM

similar to linear system identification. A huge advantage of the databased approach is the amount of time saved compared to the standard approach of simplifying a mean value model. Based on the (nonlinear) LPV model a NMPC was designed which makes necessary an additional system simulation and a condensing step each sampling instant compared to a standard linear MPC. Simulation results of the NMPC compared to a standard linear MPC show the superior tracking performance in the two variables, fresh air mass flow and boost pressure. Future work will be to test the NMPC algorithm on the test bench in order to get real-time results beside the simulation results and to get a better feeling for the computational issue of this NMPC approach.

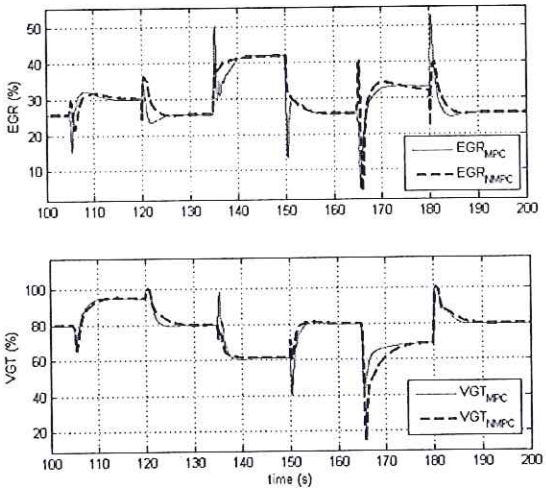


Fig. 11. Control Signals for Tracking on MVM

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