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Direct C/GMRES Control of The Air Path of a Diesel Engine

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Abstract: The continuously increasing demands in terms of performance, environmental compatibility and safety motivate the growing interest for optimal control in automotive systems. In practice, however, these methods are seldom used, one of the reasons being the nonlinear nature of the plant which makes the computation more difficult. Several nonlinear optimal control methods have been tested for automotive systems, either starting from the optimization problem in terms of a Hamilton Jacobi Bellman equation or as a nonlinear extension of well established model predictive approaches. In this paper, we apply a method which in some sense combines both worlds, the C/GMRES method. In our implementation, no physical model is used but a nonlinear NARX model is derived from data. The resulting control law is applied to a production Diesel engine and tested against the production controller, showing the potential performance of the suggested method but also the design simplicity.

1. INTRODUCTION

Automotive industry is characterized by very high and conflicting requirements, e.g. both safety and fuel efficiency are requested, but most measures for improved safety affect negatively fuel efficiency. Not surprisingly, optimization has been an important topic for a long time, but has been mostly addressed empirically, using complex control structures with many degrees of freedom and determining the optimal parameter values with an enormous experimental effort, frequently supported by specialized tools like CAMEO [1].

Against this background, there has been a substantial interest in exploring the use of model based optimal techniques to control automotive systems. In practice, only few industrial systems have been developed, e.g. by Honeywell (Stewart et al. (2010)) and Hoerbiger (Ängeby et al. (2010), for a special application), and both of them based on linear model predictive control, which yields a suboptimal solution, but allows taking explicitly in account bounds on the inputs and constraints on the state or output variables. Nonlinear optimal control has not been considered for long time, mainly because the existing approaches for the solution of the nonlinear optimal control problem are limited to a very small number of cases, and available models hardly fulfill with these conditions.

A way out of this problem may consist in looking for classes of models which do fulfill the conditions and are still able to capture the nature of a plant. This prevents, of course, the use of first principle models. In this paper, we use polynomial models, which, however, suffer from the problem that the number of parameters increases very fast with the order of the model and the degree of the polynomial expansion, leading to the well known problems of overparametrization, i.e. to models which tend to perform poorly in validation. To cope with these problems, an iterative method has been developed which exploits design of experiment (DOE) and pruning methods to derive a simple and well conditioned model of of low order and degree Hirsch and del Re (2010a). This method has been used and validated in a variety of applications (see e.g. Stadlbauer et al. (2012) and Passenbrunner et al. (2014)) in automotive control. The simple nature of these models is also well suited as a basis for nonlinear optimal control design. An example of this combination has been shown in Sassano et al. (2012), in which such a model has been used for the design of an optimal control based on a relaxed Hamilton Jacobi Bellman (HJB) equation, which has been proven to work both in simulation and practice. However, this optimal control method does not allow easy consideration of constraints and/or bounds, and at the end of the day it is not completely clear which cost function is optimized.

In this paper, we examine the possible use of a different technique, C/GMRES by Ohtsuka (2004), which also starts from a general nonlinear optimal control setup, but then combines the continuation method (see, e.g., Richter and DeCarlo (1983)) and GMRES (generalized minimum residual method) (see, e.g., Kelley (1995)) to update a time-varying optimal solution efficiently. Instead of standard Newton's method for solving optimality conditions, the continuation method is employed to derive a differential equation of the time-varying optimal solution, which can be integrated in real time with no iterative search. Then, GMRES is applied to solve a linear equation

[1] `http://www.avl.com/cameo`

for the derivative of the optimal solution with respect to time. GMRES can be implemented without computing the Jacobian matrix of the optimality conditions explicitly because it involves only a Jacobian-vector product that can be approximated by forward difference. This Jacobian-free property of GMRES reduces computational cost significantly and contrasts with related methods, e.g., by Diehl et al. (2005) based on the KKT matrix.

This paper combines the C/GMRES method with the polynomial modelling approach of Hirsch and del Re (2010a) and shows its viability for a reference automotive application which is shortly presented in the next section. Then the key elements of the C/GMRES method are summarized, the adaptation of the nonlinear discrete time model produced by the procedure of Hirsch and del Re (2010a) to the continuous time setup of C/GMRES according to Sassano et al. (2012) explained and experimental results shown, in which the performance of the examined method is compared to the behavior of the production engine control unit (ECU). This comparison confirms that the approach is a viable alternative to heuristic design, and it can be performed in a fully systematic way, starting from the data acquisition and ending at the final measurements.

2. THE TEST SYSTEM

In this work a well studied application, the air path control of a Diesel engine, is used. The specific setup includes a 2 liter 4 cylinder passenger car turbocharged Diesel engine meeting the EU5 emission legislation, equipped with a common rail injection system, a variable geometry turbine turbocharger with charge air cooling and cooled high pressure exhaust gas recirculation and standard production sensors, in particular an air mass flow sensor (a hot film anemometer), a wideband lambda sensor, pressure and temperature sensors in the intake manifold (see figure 1 for a schematic representation of the engine control setup). The engine is operated on a highly dynamical AVL testbench which, on one side, guarantees constant operation conditions - constant ambient temperature independently from the dissipated heat and constant temperature and humidity of the intake air, and on the other side connects several additional lab grade measurement system[2]. Figure 2 shows the basic structure.

The control problem to be used here consists of imposing a given value to the fresh air intake (MAF) coming into the engine via the compressor from the environment and the intake manifold pressure (MAP). These two quantities are probably the most frequently used ”leading” quantities of combustion because the air path dynamics is the dominating time constant in a Diesel engines and these two quantities are accessible on all engines. Other choices, for instance using the exhaust recirculation (EGR) rate, are also possible, but require more complex model computation as direct measurement is hardly possible.

The MAP/MAF profile can be imposed in several ways, we consider here a two inputs/two outputs setup, the inputs being the turbine vane position (which defines the efficiency of the compressor and thus directly affect the fresh intake air) and the EGR valve position, which together with the incoming fresh air determines the mass flow and chemical/thermal composition

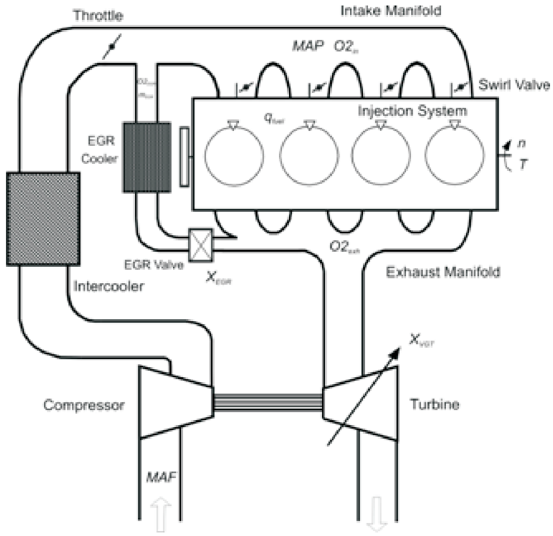

Fig. 1. Schematic representation of the engine control structure

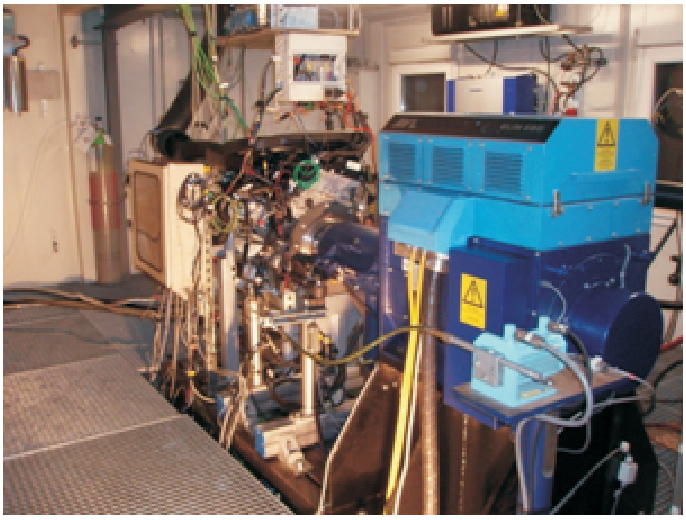

Fig. 2. Photograph of the Dynamical Engine Test Bench

of the gas mixture entering the cylinder prior to injection. Of course, a balance will setup, as the injected and burnt fuel will determine the exhaust enthalpy and thus together with the other setpoint fix the overall operating conditions of the engine.

In this study, as the key interest is the performance of the control algorithm, we shall assume the injection and speed to be given and concentrate on the steps of the reference quantities (MAP and MAF).

3. DATA DRIVEN MODELLING

Air path modelling has been the topic of very many papers, see e.g. Eriksson and Nielsen (2014) for an updated overview. There have also been attempts to derive control suited models, e.g. using LPV methods (Jung and Glover (2003)), but most of the models are not suitable for nonlinear control. Instead of first setting up a model and looking for a suitable approximation, we propose to look directly for a suitable approximation. The model used in this work was identified using the method described in Hirsch and del Re (2010a). This method starts by considering a polynomial NARX model defined as

[2] See `http://desreg.jku.at/newpage/equipment/testbenches/` for details.

$$y(k) = [y(k-1) \ \dots \ y(k-n_y) \quad u_1(k-1) \ \dots \ u_1(k-n_{u,1}) \\ u_2(k-1) \ \dots \ u_2(k-n_{u,2}) \ u_r(k-1) \ \dots \ u_r(k-n_{u,r})]^T . \tag{1}$$

where l is the maximum degree of the polynomial function, n_y the maximum lag of the autoregressive part, corresponding to the order of the system, and n_{ui}, $i = 1...r$ the maximum lag of the input. Since the model is linear in the parameters, these estimates $\hat{\theta}$ can be computed using standard least squares algorithms minimizing the sum of the squared prediction error over N measured samples (see e. g. Ljung (1999)). In general such a model assumption for a polynomial system will contain some regressors with little relevance leading both to an unnecessary model complexity and to a poor numerical condition. Hirsch and del Re (2010a) suggests an iterative procedure in which a D-Optimal design is used, i.e.

$$u^*(k) = \arg \max_{u(k)\in\Omega} \det(M), \quad k = 1 \dots N, \tag{2}$$

where $\Omega \subset \mathbb{R}^R$ defines the closed input set that is allowed for input the design, by maximizing the determinant of M. M is defined in general as

$$M = \mathrm{E}\left\{ \frac{1}{\sigma^2} \sum_{k=1}^{N} \frac{\partial f^l(x(k),\theta)}{\partial \theta} \frac{\partial f^l(x(k),\theta)}{\partial \theta^T} \right\}, \tag{3}$$

where $\mathrm{E}\{\cdot\}$ indicates the expected value. Finally, for the specific case, we obtain a polynomial model of second degree and order two with two control inputs and two measured variables, whose performance is shown in figure 3. For more details, see Hirsch and del Re (2010b). In the following, we shall not consider the dependency on injection mass and speed, because they are fixed variables in our experiments.

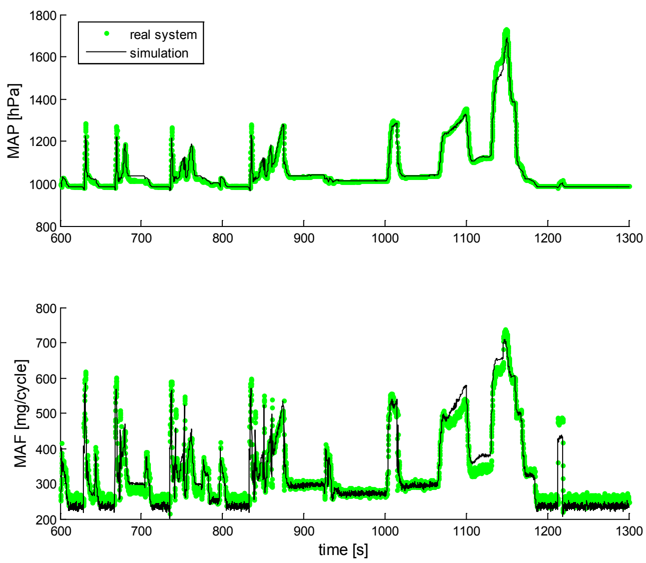

Fig. 3. Comparison of the measurements and simulation of the polynomial model used

4. THE C/GMRES METHOD

As much interest has arisen concerning the use of predictive control in automotive applications (see e.g. del Re et al. (2010)), it may be sensible to compare the examined method in the MPC framework. In the nonlinear MPC problem, we assume that the state equation and equality constraint are described by

$$\dot{x} = f(x(t), u(t)),$$
$$C(x(t), u(t)) = 0,$$

with the state vector $x(t) \in \mathbb{R}^n$ and the input vector $u(t) \in \mathbb{R}^m$. Then, an optimal control problem is solved at each time t as follows. Regarding $x(t)$ as the initial state, we consider the minimization of a performance index

$$J = \varphi(x(t+T)) + \int_t^{t+T} L(x(\tau), u(\tau))d\tau,$$

where T is the horizon length. The prediction horizon is defined from the current time t x to time $t+T$. Then, the optimal control input $u^*(\tau)$ for minimizing J is calculated within $\tau \in [t, t+T]$, and only the initial value of $u^*(\tau)$ is used as the actual control input $u(t)$ at time t.

An inequality constraint can either be transformed into an equality constraint by introducing a dummy input (see Seguchi and Ohtsuka (2003) for details) or be incorporated by adding a barrier function in the performance index.

C/GMRES Ohtsuka (2004) combines the continuation method and GMRES for tracing efficiently a time-varying solution of a nonlinear algebraic equation with time-dependent parameters. For details of the continuation method and GMRES, see, e.g., Richter and DeCarlo (1983) and Kelley (1995), respectively. Dividing the horizon into N steps, discretizing the prediction horizon and calculating the variations, at each time, the optimal control problem results in a nonlinear algebraic equation

$$F(U(t), x(t), t) := \begin{bmatrix} \frac{\partial H}{\partial u}(x_0^*(t), u_0^*(t), \lambda_1^*(t), \mu_0^*(t)) \\ C(x_0^*(t), u_0^*(t)) \\ \vdots \\ \frac{\partial H}{\partial u}(x_{N-1}^*(t), u_{N-1}^*(t), \lambda_N^*(t), \mu_{N-1}^*(t)) \\ C(x_{N-1}^*(t), u_{N-1}^*(t)) \end{bmatrix} = 0, \tag{4}$$

where $x_i^*(t)$, $\lambda_i^*(t)$, $u_i^*(t)$ and $\mu_i^*(t)$ represent the state of ith step starting from $x(t)$, the costate, the control input and Lagrange multiplier associated with the equality constraint, respectively. Let H denote the Hamiltonian defined by

$$H(x, u, \lambda, \mu) := L(x, u) + \lambda^{\mathrm{T}} f(x, u) + \mu^{\mathrm{T}} C(x, u).$$

A vector $U(t)$ is defined as

$$U(t) := [u_0^{*\mathrm{T}}(t) \ \mu_0^{*\mathrm{T}}(t) \ \cdots \ u_{N-1}^{*\mathrm{T}}(t) \ \mu_{N-1}^{*\mathrm{T}}(t)]^{\mathrm{T}},$$

where only $u_0^{*\mathrm{T}}(t)$ is used as the actual input to the system. Note that $x_i^*(t)$ and $\lambda_i^*(t)$ in (4) are determined as functions of $U(t)$ and $x(t)$ by the Euler-Lagrange equations:

$$x_{i+1}^*(t) = x_i^*(t) + f(x_i^*(t), u_i^*(t))\Delta\tau, \tag{5}$$
$$x_0^*(t) = x(t), \tag{6}$$
$$\lambda_i^*(t) = \lambda_{i+1}^*(t) + \left(\frac{\partial H}{\partial x}\right)^{\mathrm{T}} (x_i^*(t), u_i^*(t), \lambda_{i+1}^*(t), \mu_i^*(t))\Delta\tau, \tag{7}$$
$$\lambda_N^*(t) = \left(\frac{\partial \varphi}{\partial x}\right)^{\mathrm{T}} (x_N^*(t)), \tag{8}$$

where $\Delta\tau := T/N$ denotes the discretization step of the horizon, which is not necessarily identical to the sampling period in the implementation of MPC. Note that the sequence of the state over the horizon $\{x_i^*\}_{i=0}^N$ is determined recursively by (5) starting from (6) and then the sequence of the costate $\{\lambda_i^*\}_{i=1}^N$ is determined backward by (7) starting from (8).

At each time t, the nonlinear equation $F(U(t),x(t),t)=0$ needs to be solved with respect to $U(t)$ for the measured state $x(t)$. Since such an iterative algorithm as Newton's method is computationally demanding, we employ the continuation method to trace the time-varying solution with no iterative search. Note that F is identically zero if the following conditions hold:

$$F(U(0),x(0),0)=0, \tag{9}$$

$$\dot{F}(U(t),x(t),t)=-\zeta F(U(t),x(t),t) \quad (\zeta>0). \tag{10}$$

Equation (10) yields the following linear equation for $\dot{U}$.

$$\frac{\partial F}{\partial U}\dot{U}=-\zeta F-\frac{\partial F}{\partial x}\dot{x}-\frac{\partial F}{\partial t} \tag{11}$$

If $U(t)$ is calculated by numerically integrating $\dot{U}$ to satisfy (10), no iterative solution method such as Newton's method is needed. The linear equation for $\dot{U}$ is solved efficiently by GMRES, in which computation of the Jacobian matrix of the optimality conditions is not necessary because of the forward difference approximation of a Jacobian-vector product.

For finding $U(0)$ with a small amount of computation such that (9) holds, the horizon length T can be chosen to be time-dependent function $T(t)$ such that $T(0)=0$ and $T(t)$ converges smoothly to a prescribed constant T_f. Then, (9) reduces to an equation of a small size because $x_0^*(0)=\cdots=x_N^*(0)=x(0)$, $\lambda_1^*(0)=\cdots\lambda_N^*(0)=(\partial\varphi/\partial x)^{\mathrm{T}}(x(0))$, $u_0^*(0)=\cdots=u_{N-1}^*(0)$, and $\mu_0^*(0)=\cdots=\mu_{N-1}^*(0)$ hold for $T(0)=0$.

5. ADAPTATION OF POLYNOMIAL NARX MODEL TO THE C/GMRES FORMULATION

Since the C/GMRES model has been developed in a continuous domain framework in the preceding section, here we shall illustrate the main sufficient steps to transform the in/output recursive polynomial NARX problem into the state-input continuous-time description following Sassano et al. (2012). This includes some steps must be performed. We consider in this paper to the polynomial (second degree) NARX problems having the multiple output multiple input (MIMO) as described previously. Hereafter we name respectively as n_y and m_u the dimensions of the observed space y and the input u. For the sake of clarity, we rewrite the general i-th component $(i=1,\dots,n_y)$ as:

$$\begin{aligned} y^i(k) &= F^i_{y_0^i\Theta,\Gamma}(y(k-1),u(k-1),y(k-2),u(k-2))) = \\ &= y_0^i+\Theta_1^i y(k-1)+\Theta_2^i u(k-1)+ \\ &\quad +y(k-1)^T\Theta_3^i y(k-1)+u(k-1)^T\Theta_4^i y(k-1)+ \\ &\quad +u(k-1)^T\Theta_5^i u(k-1)+\Gamma_1^i y(k-2)+\Gamma_2^i u(k-2)+ \\ &\quad +y(k-2)^T\Gamma_3^i y(k-2)+u(k-2)^T\Gamma_4^i y(k-2)+ \\ &\quad +u(k-2)^T\Gamma_5^i u(k-2) \end{aligned} \tag{12}$$

where $y_0^i\in\mathbb{R}$, $\Theta_1^i,\Gamma_1^i\in\mathbb{M}^{1\times n_y}$, $\Theta_2^i,\Gamma_2^i\in\mathbb{M}^{1\times m_u}$, $\Theta_3^i,\Gamma_3^i\in\mathbb{M}^{n_y\times n_y}$, $\Theta_4^i,\Gamma_4^i\in\mathbb{M}^{m_u\times n_y}$ $\Theta_5^i,\Gamma_5^i\in\mathbb{M}^{m_u\times m_u}$. Each of previous matrix parameters is a rearrangement of those in the θ description (3).

As already observed in Sassano et al. (2012) to break the recoursivity of the model (12) it is sufficient to double the dimension of the state space representation and to apply the following transformation. Setting $n=2n_y$ the dimension of the state space representation we can write for $i=1\dots n$ the following relations:

$$x^{2i-1}(k):=y^i(k-2),\; x^{2i}(k):=y^i(k-1)-\phi^i(k) \tag{13}$$

where the n_y functions ϕ^i are defined by:

$$\begin{aligned} \phi^i(k) &:= \Theta_2^i u(k-2)+u(k-2)^T\Theta_4^i y(k-2) \\ &\quad +u(k-2)^T\Theta_5^i u(k-2) \end{aligned} \tag{14}$$

The cross action of the coefficient of the $(k-1)$-delayed samples on the $(k-2)$ u-depending terms, has the aim of cancelling the $u(k-1)$ dependence in the state $x(k+1)$. In fact, collecting in two ordered vectors, the subset of odds $[x^{2j-1}]^i(k):=x^{2i-1}(k)$, $i=1,\dots,n_y$ and evens $[x^{2j}]^i(k):=x^{2i}(k)$, $i=1,\dots,n_y$ components of x, the explicit expression of (13) evaluated on (k+1) reduces to:

$$\begin{aligned} x^{2i-1}(k+1) &= y^i(k-1)=x^{2i}(k)+\phi^i(k)= \\ &= x^{2i}(k)+\Theta_2^i u(k-2)+ \\ &\quad +u(k-2)^T\Theta_4^i x^{2j-1}(k)+ \\ &\quad +u(k-2)^T\Theta_5^i u(k-2)+ \\ &=: \tilde{F}^{2i-1}(x(k),u(k-2)) \end{aligned} \tag{15}$$

where we have used that $y(k-2)=x^{2j-1}(k)$

$$\begin{aligned} x^{2i}(k+1) &= y^i(k)-\phi^i(k+1)= \\ &= \big[y_0^i+\Theta_1^i y(k-1)+\Theta_2^i u(k-1)+ \\ &\quad +y(k-1)^T\Theta_3^i y(k-1)+ \\ &\quad +u(k-1)^T\Theta_4^i y(k-1)+ \\ &\quad +u(k-1)^T\Theta_5^i u(k-1)+ \\ &\quad +\Gamma_1^i y(k-2)+\Gamma_2^i u(k-2)+ \\ &\quad +y(k-2)^T\Gamma_3^i y(k-2)+ \\ &\quad +u(k-2)^T\Gamma_4^i y(k-2)+ \\ &\quad +u(k-2)^T\Gamma_5^i u(k-2)\big]+ \\ &\quad -\big[\Theta_2^i u(k-1)+u(k-1)^T\Theta_4^i y(k-1)+ \\ &\quad +u(k-1)^T\Theta_5^i u(k-1)\big] \\ &= y_0^i+\Theta_1^i y(k-1)+y(k-1)^T\Theta_3^i y(k-1)+ \\ &\quad +\Gamma_1^i y(k-2)+\Gamma_2^i u(k-2)+ \\ &\quad +y(k-2)^T\Gamma_3^i y(k-2)+ \\ &\quad +u(k-2)^T\Gamma_4^i y(k-2)+ \\ &\quad +u(k-2)^T\Gamma_5^i u(k-2) \\ &= y_0^i+\Theta_1^i\tilde{F}^{2j-1}+(\tilde{F}^{2j-1})^T\Theta_3^i\tilde{F}^{2j-1}+ \\ &\quad +\Gamma_1^i x^{2j-1}(k)+\Gamma_2^i u(k-2)+ \\ &\quad +x^{2j-1}(k)^T\Gamma_3^i x^{2j-1}(k)+ \\ &\quad +u(k-2)^T\Gamma_4^i x^{2j-1}(k)+ \\ &\quad +u(k-2)^T\Gamma_5^i u(k-2)= \\ &=: \tilde{F}^{2i}(x(k),u(k-2)) \end{aligned} \tag{16}$$

Then *formally* we can write:

$$x(k+1)=\tilde{F}(x(k),u(k-2)) \tag{17}$$

where $\tilde{F}:\mathbb{R}^n\times\mathbb{R}^{m_u}\to\mathbb{R}^n$ and his components are defined by the last equality in (15) and (16)

We can imagine to treat the sample $u(k-2)$ as a parameter or equivalently impose the hypothesis that it does not vary so much in the interval $[t_k, t_{k-2}]$. Substituting $u(k-2) = v$ the (17) can be rewritten this way:

$$x(k+1) = \tilde{F}(x(k), v) \tag{18}$$

and by approximating $\dot{x}$ with his relative Explicit-Euler T-discrete approximation $\dot{x} \sim (x(k+1) - x(k))/T, \quad x(k) \sim x(t)$ it is possible to identify the following differential equation:

$$\dot{x}(t) = \frac{1}{T}(-x(t) + \tilde{F}(x(t), v)) \tag{19}$$

Finally, according to the preceding observation for which $(u(k) \sim u(k-1) \sim u(k-2)))$ we can refix the time-dependence of the parameter v by $v = u(t)$ and obtain a system in the C/GMRES desired framework:

$$\dot{x}(t) = \hat{f}_T(x(t), u(t)) := \frac{1}{T}(-x + \tilde{F}(x(t), u(t))) \,. \tag{20}$$

where the parameter T should be taken sufficiently small. Note that this value is independent from the time horizon considered by the C/GMRES method.

6. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed method we need a reference. As the tested engine is currently in production and using on several passenger cars, we have chosen to use the engine control unit (ECU) as a reference and to compare the performance of the new algorithm with the standard values. Notice that in practice this is done by having the ECU running as usual, but using a special software designed by the ECU provider to the vehicle developer to bypass parts of it. In this case, ECU computes all values as usual, including the VGT and EGR references, but these values are overwritten by our algorithm which runs on a dSpace station. In practice, this means that the ECU works as usual, but these two outputs are replaced by our values. Figure 4 shows the experimental results obtained both the standard production ECU and by C/GMRES method. Figure 5 shows for better clarity the tracking error of both methods. The lower part of figure 4 shows the different way in which actuators are used by the two methods.

In general, C/GMRES performs slightly better than the standard ECU, and uses the (nonlinear) actuators in a quite different and more efficient way. The average cumulated square error of the C/GMRES method is 74% of the error of the ECU for MAP and 89% for MAF. Taking in account the fact that the sampling time of the C/GMRES control was significantly longer (50 msec vs. 20 msec) than the ECU, and that the data are transmitted from dSpace to the ECU output buffers by CAN, they are very promising.

7. CONCLUSION AND OUTLOOK

The presented results show are based on a first implementation of C/GMRES but still it already slightly outperforms the production ECU for the considered steps. Of course the comparison is not exhaustive, as several other criteria, like emissions, noise, vibration should be evaluated in order to evaluate the whole performance. Furthermore, usually the ECU can be operated using three control quantities (the same two as used here plus a throttle valve), which, for easiness of comparison with other results, has not been done here. Still the C/GMRES based controller is not completely tuned.

However, the very great advantage is the systematic and fast development procedure - the model can be derived typically in two hours and the control tuned in a few hours as well. The comparison with the performance of the ECU - which is tuned in a long and tedious calibration process - becomes a completely different flavor, and we do expect similar improvements in terms of emissions, due to the use of actuators, which could not be inserted in this draft for lack of time, but will be included in a possible final version.

In a next step, the use of a discrete time version of this method will be used to avoid the discrete to continuous transformation step.

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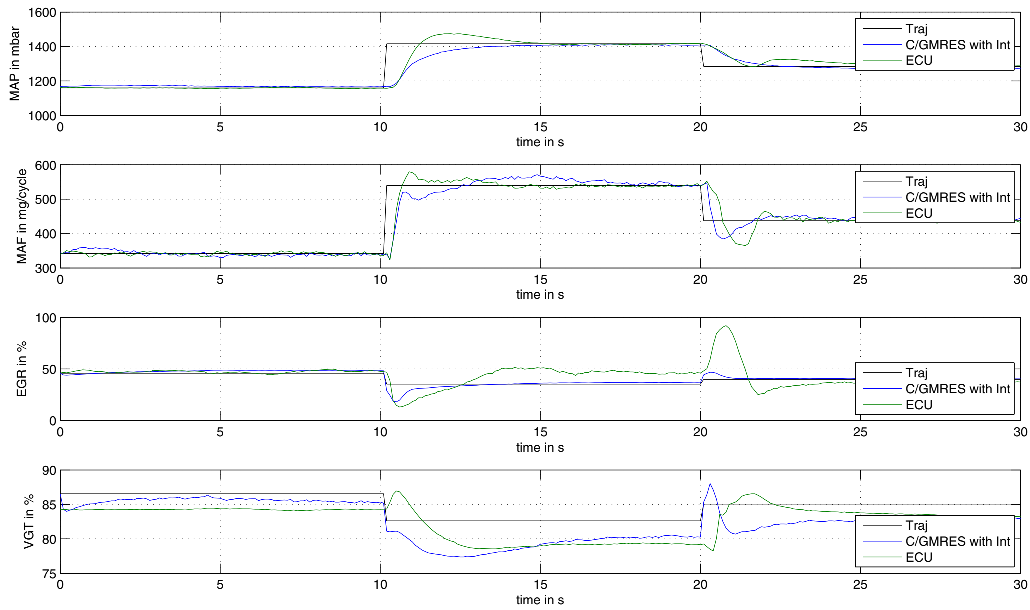

Fig. 4. Comparison of the performance of the proposed approach and the standard production ECU

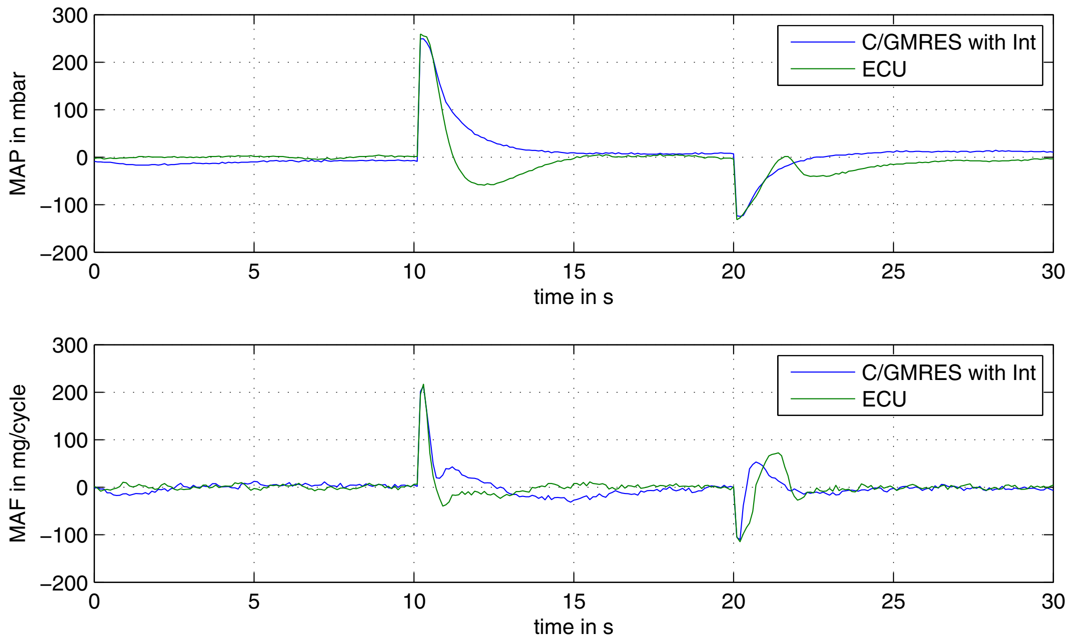

Fig. 5. Control errors of the proposed approach and the ECU

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