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Self-tuning NMPC of an Engine Air Path

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Abstract: Many automotive systems such as engines have manufacturing tolerances or change over time. This limits the performance of controllers tuned for the nominal case. A robust controller can not always overcome this performance gap. Against this background, in this work, we propose a self-tuning control strategy for an engine air path model obtained from data of a real engine and show its benefits setting. The self-tuning control consists of an online parameter estimation algorithm for polynomial non-linear autoregressive with exogenous input (PNARX) models and a nonlinear model predictive controller (NMPC) implemented by the continuation/generalized minimum residual (C/GMRES) algorithm. In a first step design of experiments (DOE) is utilized to identify a PNARX model offline from measurements performed on an engine test bed. A tracking NMPC is designed for this model and applied in simulation on the identified model. The control performance is assessed for the case of a wrong initial guess. It is shown that the resulting performance gap can be overcome by the online parameter estimation of a k-step prediction model with directional forgetting. An improved closed loop control performance of the air path model confirms the approach.

Keywords: automotive control, system identification, adaptive control, predictive control

1. INTRODUCTION

The control of complex automotive systems such as internal combustion engines is a challenging task due to very high demands and conflicting requirements, e.g. fuel economy and pollutant emissions. In order to cope with this. modern Diesel engines have evolved to highly complicated systems with many degrees of freedom for control.

The achievable performance in optimal control is strongly related to the quality of the underlying model used for optimization. Most physical systems require nonlinear models to represent them precisely enough, see e.g. del Re et al. (2010), Oliden et al. (2017a). First-principle models are often too complex for control design whereas simplified models on their basis tend to be imprecise, see Sassano et al. (2012). In the case of engine systems, we have two more factors which make the use of first-principle models less straightforward: they are produced on a large scale, within important manufacturing tolerances, and are subject to changes over time, mainly due to aging. All this motivates our interest on data based models for control, which can be tuned more easily to the specific system, and more specifically on the class of non-linear autoregressive models with exogenous input (NARX), especially the polynomial NARX (PNARX) models. They were already successfully applied both for offline identification of an air path model, see Hirsch and del Re (2010b), as well as to design approximate optimal controls and receding-horizon optimal controls Blumenschein et al. (2015). For offline identification a design of experiments (DOE) based iterative algorithm for PNARX models is used to determine the model, see Hirsch and del Re (2010a),Hirsch (2012).

Model predictive control (MPC) is a very well established method to control multi-variable systems considering constraints, see e.g. Rawlings and Mayne (2009); Oliden et al. (2017a); Hernandez et al. (2014). MPC for air path control was developed by several authors, for instance Ortner and del Re (2007). In Sassano et al. (2012) a dynamic control law was derived for the PNARX air path model based on the solution of the Hamilton-Jacobi-Bellman equation (HJB), see e.g. Anderson and Moore (1989). A nonlinear MPC (NMPC) based on the C/GMRES algorithm by Ohtsuka (2004) was used in Gagliardi et al. (2014), while Blumenschein et al. (2015) modified the C/GMRES algorithm for identified models.

This work extends the state of the art by an online identification algorithm able to react to changing system behavior or to tune an initial model to the actual parameters. Differently from the previous works, the identification cost function is changed from 1-step prediction to k-step prediction, as proposed in Schrangl et al. (2019b) inspired by the offline one presented in Farina and Piroddi (2010); Piroddi and Spinelli (2003), and then extended with a directional forgetting scheme in Schrangl et al. (2019a).

The contribution of this paper is to combine the identification algorithm with directional forgetting with the C/GMRES algorithm for discrete-time IO models and

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show the advantages of this adaptive control scheme on the practical example of a production engine.

2. SYSTEM AND EXPERIMENTAL SETUP

2.1 Air path of a turbocharged Diesel engine

A scheme of the air path of a turbocharged Diesel engine is shown in fig. 1. The air path is equipped with a variable geometry turbocharger (VGT) and an exhaust gas recirculation system (EGR).

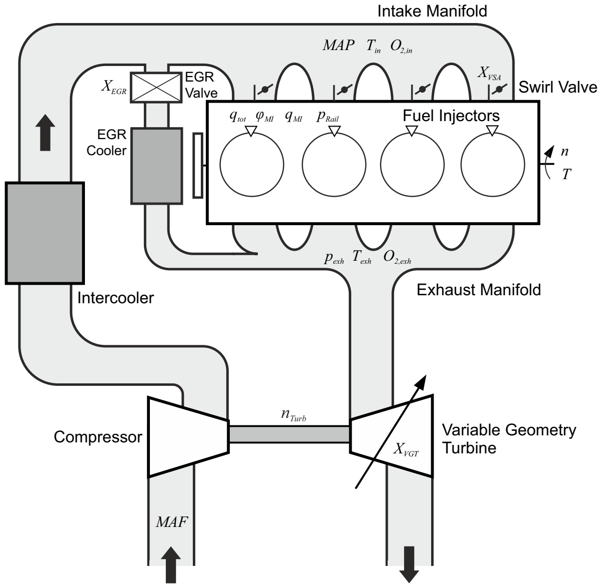

Fig. 1. Scheme of the air path system of a modern Diesel engine

Fresh ambient air enters the engine via the air filter, compressor, intercooler and intake manifold. The pressure of the fresh air is increased by the compressor, while the density is raised by the intercooler. When the EGR valve is open, the fresh air in the intake manifold is mixed with a portion of recirculated exhaust gases. The gas mixture enters the combustion chambers by the intake ports. After closing the intake ports, the fuel is injected around the top dead center of the piston movement. After the combustion the major fraction of the hot exhaust gases leaves the internal combustion engine through the turbine which recovers part of the exhaust energy content. For further details see e.g. Heywood (1988).

The vane position X_{VGT} of the turbocharger and the EGR valve opening level X_{EGR} are the control inputs, the mass air flow *MAF* and the pressure *MAP* in the intake manifold (IM) are the controlled variables (outputs). The fuel injection amount m_{f} and the resulting engine speed n are treated as disturbance inputs of the system. This leads to a multi-input multi-output (MIMO) system with 4 inputs and 2 outputs, see fig. 2 and table 1. The air path is a strongly coupled system mainly due to the turbocharger.

2.2 PNARX model

Let the system input be denoted by $u_k \in \mathbb{R}^{n_{\mathrm{u}}}$ and the output by $y_k \in \mathbb{R}^{n_{\mathrm{y}}}$, where $k \in \mathbb{Z}$ is the time instant. The i-the input and output components are denoted $u_k^{(i)}$ and $y_k^{(i)}$.

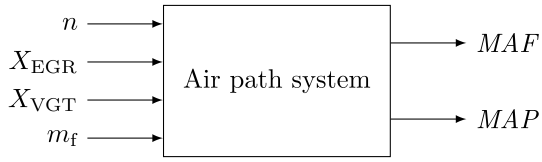

Fig. 2. Control view of the air path system

Table 1. Inputs and outputs of the air path model

Description	Symbol	Unit	Value range min.	Value range max.
Inputs				
Engine speed	n	min^{-1}	800	3000
EGR valve position	X_{EGR}	%	0	100
VGT guide vane position	X_{VGT}	%	60	95
Injected fuel per cycle	m_{f}	mg	0	45
Outputs				
IM air mass flow per cycle	*MAF*	mg	0	1800
IM air pressure	*MAP*	mbar	800	3500

Then $\mathcal{M}(\theta)$ is the discrete-time, parametric, polynomial prediction model, with i-th model output

$$\mathcal{M}(\theta) : \hat{y}_k^{(i)} = \hat{f}_{p_i}(x_k)^\intercal \theta_i \quad \forall i \in \{1, \ldots, n_{\mathrm{y}}\} \tag{1}$$

$$y_k^{(i)} = \hat{y}^{(i)} + e_k \tag{2}$$

with $x_k = [\mathrm{vect}(U_k)^\intercal \ \mathrm{vect}(Y_k)^\intercal]^\intercal$, $Y_k = [y_{k-i}]_{i=1}^{m_{\mathrm{y}}}$, $U_k = [u_{k-i}]_{i=0}^{m_{\mathrm{u}}-1}$, where $\mathrm{vect}(\cdot)$ vectorizes a matrix to a column vector with all entries of that matrix and

$$\hat{y}_k = \begin{bmatrix} \hat{y}_k^{(1)} \\ \vdots \\ \hat{y}_k^{(n_{\mathrm{y}})} \end{bmatrix} \in \mathbb{R}^{n_{\mathrm{y}}}$$

are the n_{y} model outputs at time instant $k \in \mathbb{Z}$. The function $\hat{f}_{p_i}(\cdot) \in \mathbb{R}^{n_i}$ is a polynomial function of degree p_i of its scalar arguments and $\theta_i \in \mathbb{R}^{n_i}$ is the model's parameter vector for the i-th output. The variables $m_{\mathrm{y}} \geq 0 \in \mathbb{N}$ and $m_{\mathrm{u}} \geq 1 \in \mathbb{N}$ are the model orders. The model parameter vector θ is the vertical concatenation of all θ_i.

3. OFFLINE MODEL IDENTIFICATION

3.1 Model identification

Data was gathered at a dynamic engine test branch using the iterative procedure of Hirsch (2012). As an example, in fig. 4 the results obtained after applying the DOE signal for a model of degree 4 is shown. Note that there is a slight deviation between desired (setpoint; red) signals applied to the ECU and the actual measured signals (blue) obtained by the sensors/ECU.

The DOE data of degree 4 with 59 model parameters was found to be the most suitable one for the identification data set, which means that it provided the highest validation fits when the other 4 data sets were used as validation data. Both an identification of a $k = 1$ and $k = 2$ step prediction model was done using LS and the algorithm

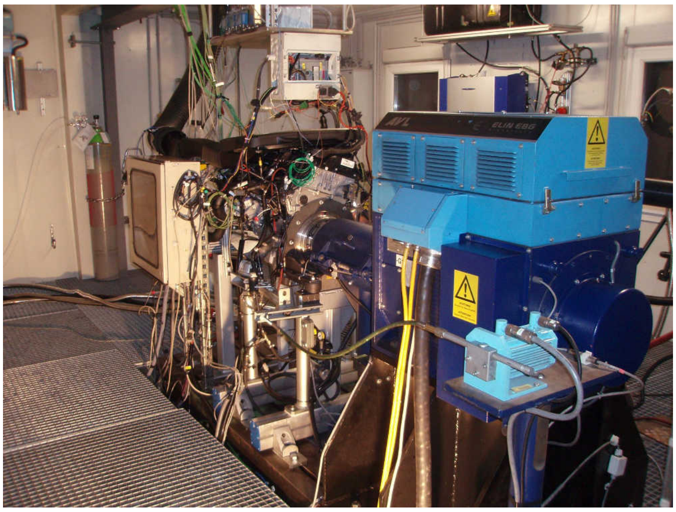

Fig. 3. Experimental setup of the engine test bench with a BMW N47 Diesel engine

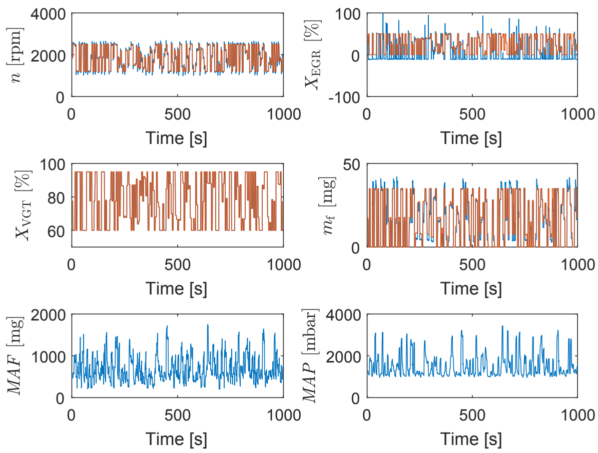

Fig. 4. Input and output signals of the engine air path for DOE inputs for a model of degree 4

of Farina and Piroddi (2010), respectively. Higher values for k would have too computationally expensibe due to the recursive nature of the model and its medium-scale complexity.

3.2 Model validation

The identified models have been validated using the other datasets and the 1-step prediction error as well as the simulation error (see Ljung (1999)) is compared. As expected, the multi-step model has a superior simulation performance compared to the 1-step model. The FIT value, defined in (Hirsch, 2012, eq. (4.88)), has been used to assess the model quality using the different validation data sets. The results are summarized in table 2. Exemplary results for the setting $k = 2$ and the WLTP data (assumed to be a realistic validation data set) are shown in fig. 5.

4. NMPC WITH OFFLINE MODEL

A nonlinear model predictive control (NMPC) for tracking reference profiles of MAF and MAP is designed using

Table 2. Model quality comparison: Validation FIT values in % for 1-step prediction and simulation using different data sets (DOE4 is the identification data set) and using k-step model identification for $k = 1$ and $k = 2$.

k	Data	Prediction		Simulation	
		MAF	*MAP*	*MAF*	*MAP*
1	DOE1	79.94	96.25	59.16	82.53
	DOE2	84.31	96.53	65.53	84.27
	DOE3	90.76	96.24	70.70	80.04
	DOE4	89.64	96.95	70.44	85.02
	WLTP	86.12	95.25	51.17	64.15
2	DOE1	79.04	96.24	64.20	83.69
	DOE2	83.39	96.54	68.58	85.18
	DOE3	89.36	96.20	77.21	80.24
	DOE4	88.15	96.93	72.62	85.32
	WLTP	83.33	95.00	66.44	66.78

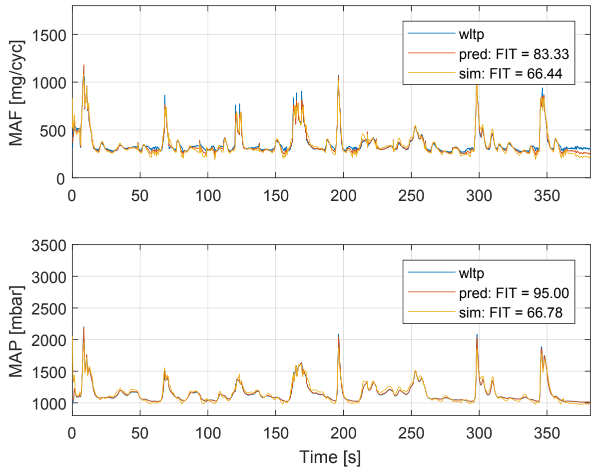

Fig. 5. Validation result (1-step prediction and simulation) for WLTP data and $k = 2$ step identification

the identified 2-step model. The fast numerical algorithm C/GMRES of Ohtsuka (2004) is used to efficiently solve the receding-horizon optimal control problem. We use the C/GMRES implementation for DT-IO models presented in Blumenschein et al. (2015). The NMPC controls only the control inputs $u_c = [X_{\mathrm{EGR}}, X_{\mathrm{VGT}}]^\intercal$, while the disturbance inputs $u_d = [n, m_f]^\intercal$ are provided as measured disturbances to the control, because they are given by the requirement of the driver.

4.1 Nominal control

The goal of the control is tracking reference trajectories for MAF and MAP, which is a standard approach and also done e.g. in the former works Sassano et al. (2012); Gagliardi et al. (2014); Blumenschein et al. (2015). We use a similar scenario as in Sassano et al. (2012), given by (almost) constant signals $n = 2000\,\mathrm{rpm}$ and $m_f = 20\,\mathrm{mg/cycle}$ and reference trajectories for MAF and MAP as filtered step sequences shown in fig. 6. The controller is applied to the identified model in simulation and in the nominal setting described in this subsection the controller has perfect model parameter knowledge. The input to the plant is denoted $u = [u_d, u_c]^\intercal$, the output is denoted

$y = [MAF, MAP]^\intercal$ and the reference signals denoted $r = [MAF_{\mathrm{ref}}, MAP_{\mathrm{ref}},]^\intercal$.

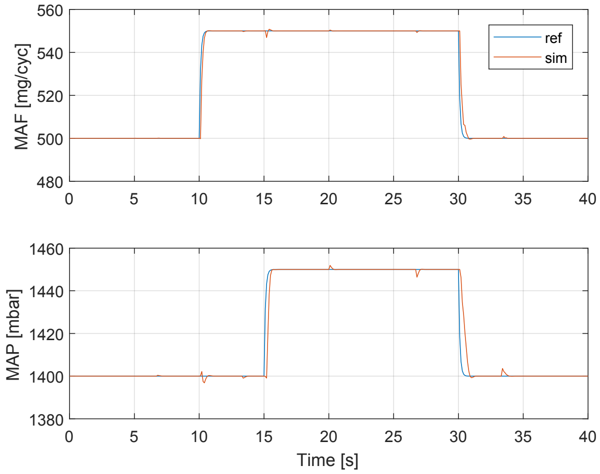

Fig. 6. Reference signals (blue) and system outputs (red) of the nominal controller applied to the identified model in simulation

The cost function of the controller at time instant t is defined as

$$J_{\mathrm{MPC}} = \varphi(\Delta y(t + n_{\mathrm{PH}})) + T_{\mathrm{s}} \sum_{k=t}^{t+n_{\mathrm{PH}}} L(\Delta y(k), \Delta u(k)) \tag{3}$$

with $\Delta y(t) = y(t) - r(t)$, $\Delta u(t) = u_{\mathrm{c}}(t) - u_{\mathrm{c}}(t-1)$, the terminal cost function

$$\varphi(\Delta y) = \Delta y^\intercal S \Delta y, \tag{4}$$

and the running cost function

$$L(\Delta y, \Delta u) = \Delta y^\intercal Q \Delta y + \Delta u^\intercal R \Delta u, \tag{5}$$

where the weighting matrices of this quadratic cost function have been set to

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, R = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}, S = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}. \tag{6}$$

For evaluating the control performance over the whole scenario of $T = 40\,\mathrm{s}$ the evaluation cost function is defined as

$$J = T_{\mathrm{s}} \sum_{t=0}^{T/T_{\mathrm{s}}} L(\Delta y(t), \Delta u(t)). \tag{7}$$

The following parameters have been used for the C/GMRES algorithm: prediction horizon $n_{\mathrm{PH}} = 10$, max. iterations of GMRES $k_{\max} = 10$, step size $h = 0.002$, stabilization parameter $\zeta = 1/h$, relative tolerance $r_{\mathrm{tol}} = 1 \times 10^{-6}$, no preconditioning, no lookahead.

This nominal control, where the model parameters in the prediction model $\hat{\theta}$ are the same as the plant model parameters θ^*, leads to the results depicted in figs. 6 and 7. The evaluation cost function leads to a value $J = 1271$ for this scenario.

4.2 Perturbation of the model used in controller

The sensitivity of the control performance was assessed with respect to wrong initial model parameters. Accord-

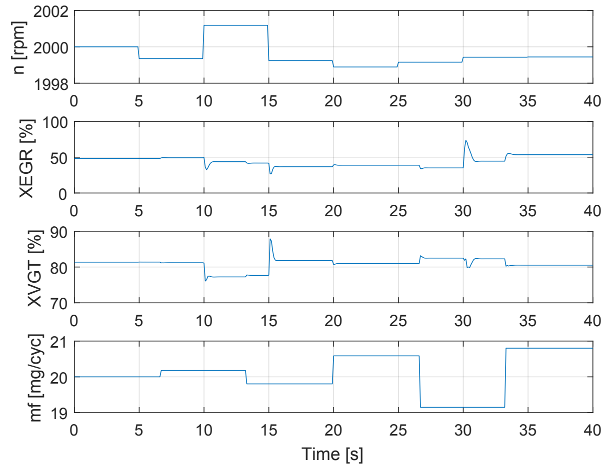

Fig. 7. Measured disturbances (n, m_{f}) feedforward-applied to the plant and control inputs $(X_{\mathrm{EGR}}, X_{\mathrm{VGT}})$ resulting from the nominal NMPC control

ingly, the prediction model in the controller $\hat{\theta}$ is disturbed by

$$\hat{\theta} = \theta^*(1 + \varepsilon \Delta\theta) \tag{8}$$

where $\Delta\theta$ is a random parameter vector from a uniform distribution in $[-1, 1]$ and ε is the gain of the disturbance. Variations up to $5\,\%$ of the nominal value have been made, i.e. $\varepsilon \in [-0.05, 0.05]$. The resulting loss in control performance is shown by evaluation the cost function J with respect to ε, which is shown in fig. 8. It can be seen that there is a high sensitivity and at the maximum performance loss (where $\varepsilon = -0.05$) the cost function value is $J = 7779$, about 6 times higher as in the nominal case. Some exemplary trajectories for this case are shown in the next section.

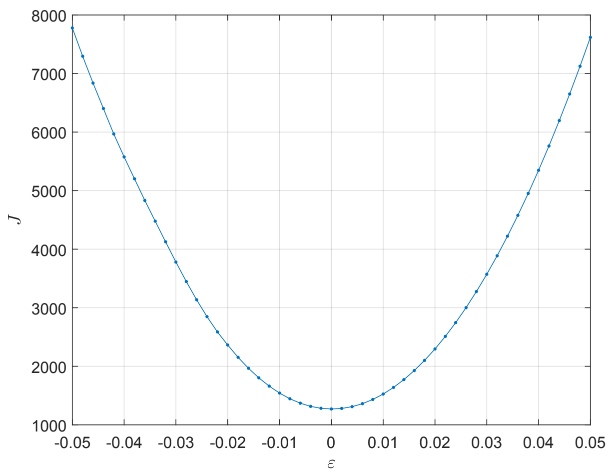

Fig. 8. Sensitivity analysis of the control performance with respect to a perturbation of the prediction model parameters in the controller by a gain ε

5. NMPC WITH ONLINE PARAMETER UPDATE

Now the NMPC is combined with the multi-step recursive LS (MS-RLS) algorithm with directional forgetting presented in (Schrangl et al., 2019a, Algorithm 1) in order to get an adaptive, self-tuning NMPC controller that is able to react to initially wrong model parameters or slowly changing system parameters over time. Directional forgetting is used in order to cope with the low information of the identification signals typically appearing in a tracking closed-loop application, as discussed in Schrangl et al. (2019a). The goal is to show that the approach is able to close the performance gap shown in the previous section by parameter adaptation. A comparison between $k = 1$ and $k = 2$ for the parameter estimation in the MS-RLS algorithm is made. The control scheme is depicted in fig. 9.

Online identification aims to estimate the parameters $\theta^{(k)}$ at each time step t using $(u(\bar{t}), y(\bar{t}))$ from $\bar{t} = 1$ up to time $\bar{t} = t$. The aim is that recursive algorithm solves the problem at each step t, and, by modification of the cost function, to extend this algorithm with a forgetting scheme to obtain an adaptive, recursive identification algorithm for k-step prediction models.

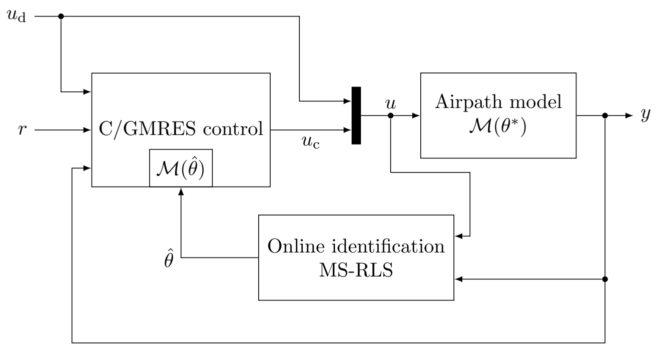

Fig. 9. Scheme of the control with online identification

The scenario (reference signals r and disturbance u_d) has been repeated $n = 5$ times while applying the self-tuning NMPC continuously for this longer scenario. In this way the cost function J can be evaluated 5 times. The result of this simulation is shown in fig. 10, where MS-RLS settings of $k = 1$ and $k = 2$ are compared to the nominal case cost (flat line).

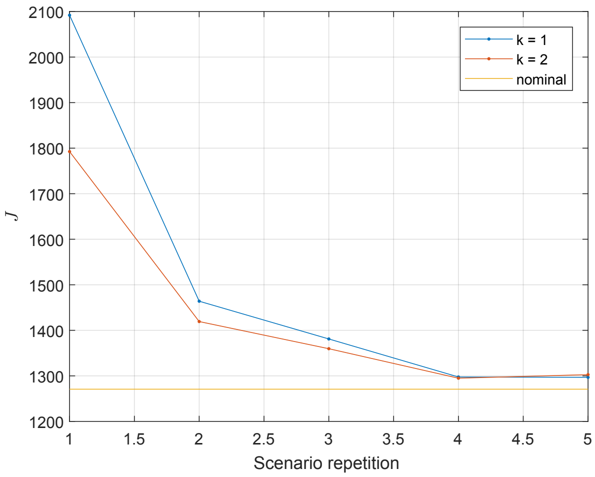

Fig. 10. Comparison of performance of online identification with nominal control (best case)

A parameter deviation with $\varepsilon = -0.05$ was used as initial parameters in the C/GMRES prediction model and MS-RLS (for which no adaptation leads to a cost function value of $J = 7779$). The following settings were used in the MS-RLS algorithm: forgetting factor $\lambda = 0.999$, directional forgetting threshold $\epsilon = 1 \times 10^{-3}$ (eq. (28) in Schrangl et al. (2019a)), tolerance (ε in Algorithm 1 of Schrangl et al. (2019a)) of 1×10^{-6}, maximum iterations 100.

Figure 11 shows exemplary results of the tracking outputs: the reference is compared with the case no adaptation ($\hat{\theta}$ constant with $\varepsilon = -0.05$), and the first and fifth repetition of the case with adaptation (MS-RLS with $k = 2$ and settings described above). It is shown that the tracking performs better with adaptation and after several repetitions the performance is close to the nominal case.

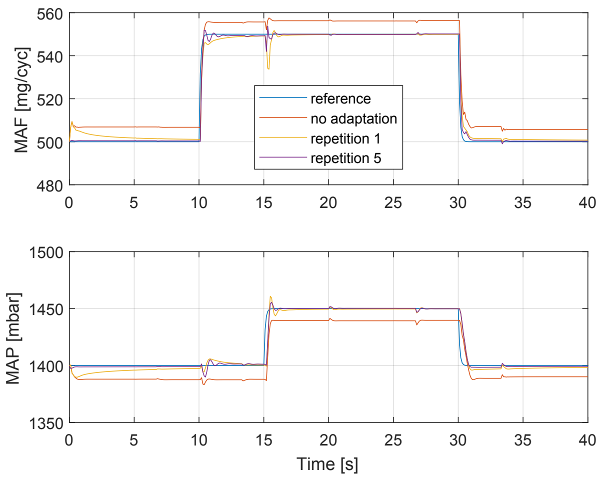

Fig. 11. Tracking signals comparison without and with adaptation

In the presented closed-loop case, however, the parameters estimated by MS-RLS do not yet converge to the true parameters of the plant, because the signals n and m_f are in a very narrow range and the algorithm with directional forgetting has too little information to estimate the parameters correctly. To show the evolution of the parameter estimate another simulation with sufficiently exciting data (step signals for all inputs in a wide range) is done and the resulting evolution in fig. 12 shows that MS-RLS with directional forgetting is able to estimate the true parameters of the plant θ^* after some time.

6. CONCLUSIONS

In this paper we have presented a possible approach to systematically design a self-tuning NMPC based on data. We show the whole toolchain to design this approximately optimal receding-horizon controller starting from DOE-based measurements to design offline models using multi-step identification to the online adaptation of the prediction model parameters in the NMPC. The simulation results confirm that a identification algorithm optimizing the k-step prediction performance is advantageous for both offline and online identification, because it leads to higher offline fits in simulation performance and tends to faster adaptation in the online case. The combination of MS-RLS with C/GMRES control shows a promising behavior

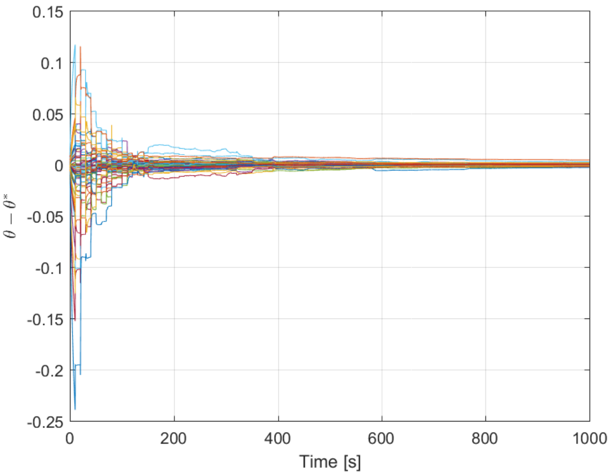

Fig. 12. Evolution of difference of estimate θ and true value θ^* with MS-RLS online identification ($k = 2$) using exciting data

for the conducted simulation studies and confirms that this approach can be useful in practice. What remains open for future research is to test the approach on the real system and compare it with other approaches.

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