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Torque Control of a Diesel Engine by an Eigenpressure Based Approach

Dominik Moser, Sebastian Hahn, Harald Waschl and Luigi del Re

Abstract— **Although the application of cylinder pressure sensors to obtain insight into the combustion process is not a novel topic itself, the recent availability of inexpensive in-cylinder pressure sensors has prompt an upcoming interest for the utilization of the cylinder pressure signal within engine control and monitoring. By the use of techniques, like principle component analysis, it is possible to reduce the high amount of data in the pressure signal during one cycle whilst preserving as much as possible of the fundamental information. Up to now this extracted information, the so called features, were mainly used for modeling tasks and virtual sensors. In this work a converse approach is proposed, namely to directly control these features to desired values by controlling the injection parameters. To this end, the relation between engine torque and features was identified and in addition also models for the relation between features and injection parameters, like the angle and amount of the main injection, were obtained. These models were then used for the active control of the features. The method was implemented on a 2L common rail Diesel engine at the testbench of the JKU Linz and led to initial results in a torque control application.**

I. Introduction

In the last decades passenger car Diesel engines have become complex systems with high numbers of actuators, like a common rail system with multiple injections or turbo chargers, and thus resulting in a large number of degrees of freedom in control design, [1]. The main task for the control, besides ensuring stable operation within safety limits, is to provide the desired engine torque while optimizing fuel economy and maintaining the compliance with the emission legislation. Up to now, typically the control task is split into several sub components, like fuel system or air system control, and often in production type engines performed by a combination of feedforward and SISO feedback loops. Due to iteratively more stringent emission limits by legislation, which correlate with increased fuel economy, the interest for advanced control concepts, like model based approaches, and also combustion modes, like partial premixed combustion (PPC) or homogeneous charge compression ignition (HCCI), has been increasing.

Moreover, the determination of closely related information about the combustion process based on in-cylinder pressure measurements has become an important topic. Although the use of cylinder pressure sensors to monitor and control the combustion is not a novel topic itself [2], recently available low cost in-cylinder pressure sensors have prompt again the interest for the implementation in production type engines. For example in [3] a cylinder pressure based combustion control for a CR Diesel engine is presented. Also for the application of advanced combustion modes, like [4], the in-cylinder pressure information is important for the control and stability of the process itself.

In a conventional Diesel engine, the in cylinder pressure signals can be used to determine quantities like the CA5, CA50, CA90[1] or the overall indicated pressure, which can be used for a cycle based feedback control of the injection system [5].These quantities are related to the heat release process and consequently the number, amount and angle of fuel injections. All those signals can be calculated out of the pressure trace, e.g. by application of heat release calculation [6].

Besides the direct use for combustion control, the pressure signal can also be utilized in virtual sensors to estimate emissions or quantities in the air system. Here the reduction of the high amount of data which is recorded during one combustion cycle[2], is an important aspect. One possibility to maintain the informative part of the signal while reducing the redundant information is the application of a principle component analysis [7], whereas a more detailed description is given in the following sections. In several works this technique was used to reduce the amount of data and design virtual sensors for NO_x ([8], [9]) or NO_x, λ and opacity [10]. Besides the use of PCA there are also other methods to extract the essential information of the pressure trace, like in [11] where a graphical signature approach was applied for a trapped cylinder mass estimation. Another different approach was used in [12] where the reduction of the data was performed manually by selection of individual features of the pressure trace, like crank angle of peak pressure. Based on these characteristics a cylinder pressure based control was applied.

In this work we propose a converse approach, namely not to use the extracted features of the cylinder pressure for a virtual sensor, but to use the main injection parameters to directly control the features in a desired way. The idea is that a set of desired features can be determined based on a virtual sensor and used for control. As manipulated variables for the control of the features the fuel amount q_{MI} and the angle of the main injection φ_{MI} were chosen.

The rest of this work is structured as follows: First the experimental setup and the system itself are described. Next the acquisition of the so called Eigenpressures with the PCA

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[1] which are corresponding to the crank angle where 5, 50 or 90 percent of the fuel was burned determined by heat release calculation

[2] e.g. if the pressure trace is recorded with a resolution of 1CAD during one combustion cycle on a 4 cylinder engine 720 measurements are obtained

approach and the determination of the different necessary models is presented. Finally a simple torque control structure which directly uses the features and identified models is introduced.

II. System description

In this work an EU5 2 liter 4 cylinder passenger car turbocharged Diesel engine was considered. The engine is equipped with a common rail injection system with multiple injections, a variable geometry turbine turbocharger with charge air cooling and cooled high pressure exhaust gas recirculation.

A. Experimental setup

The engine was operated on a highly dynamical and fully conditioned engine test bed at the Johannes Kepler University Linz. In addition to the standard engine sensors, the setup was extended with a high precision AVL Indismart Gigabit indicated pressure measurement system . With this device it is possible to record the pressure inside the combustion chamber with a resolution of 0.5 CAD, and also perform the necessary drift and offset compensation. All four cylinders were equipped with AVL GU13G14 piezoelectric pressure transducers, but in view of future production applications only one piezo electric pressure transducer was used. To this end, a balancing or cylinder individual control was not considered in this work. Moreover, the particular engine was equipped with a development ECU with a ETAS ETC bypass system which allows to directly modify parameters of the control, e.g. the fuel amount of the pilot or main injection. During the experiments also other measurement quantities, like the engine torque, rotational speed, boost pressure, were measured with additional systems (e.g. a dSpace rapid prototyping and an AVL PUMA test bench operating system). The dSpace system was also used to apply the control signals for the injection system via the ECU bypass. Here it should be mentioned that all other parameters inside the ECU were kept at production standard. The overall test layout with the corresponding connections is depicted in Fig. 1.

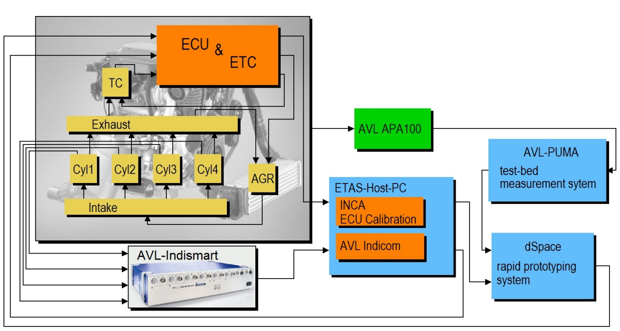

Fig. 1. Experimental setup

B. Data acquisition

In the setup two main nodes for data acquisition, with two different measurement domains can be found. Most of the data are directly recorded in the time domain by the dSpace system which is connected with ECU, testbench, and Indismart via CAN-Bus. The second node is the Indismart device itself where the in-cylinder pressure data are additionally stored in the crank angle domain. During one combustion cycle the resolution of 0.5 CAD leads to 1440 datapoints per cycle[3]. Due to this large amount of data it is not possible to send the data via the CAN-Bus directly to the dSpace system[4] and so both signals have to be synchronized during post-processing. Here it should be mentioned that in the following closed loop control application it was possible to transmit selected features of the pressure trace via the CAN-Bus. To this end, in the time domain signal on the dSpace system also the actual cycle number was transmitted and used for the synchronization.

III. Identification of models for control

First a series of steady state measurements were performed to obtain an identification dataset for the control models. To this end, the operating range of the engine, defined by engine speed and torque, was gridded into separate points to cover a wide range of the typical operating range and to provide a diverse identification dataset. These measurements were performed in 29 separate operating points and for each point 50 cycles were recorded. This led to a total amount of 1450 indicated pressure curves which were used for the identification and validation of the models. The selected operating points are presented in Fig. 2. In spite of the

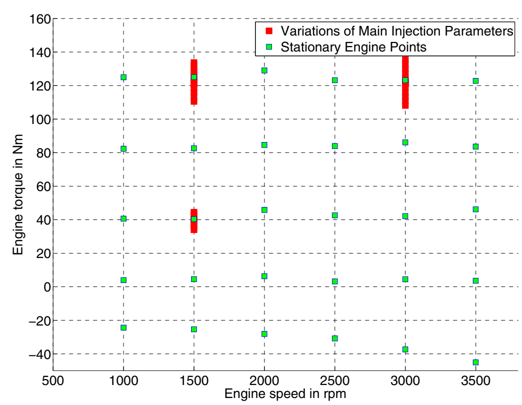

Fig. 2. Operating points used for identification

following control approach also two important parameters of the main injection, namely the amount and the angle, were varied in selected operating points. Again the task was to determine the relation between these two parameters and the engine torque and both were varied in a limited but still significant range of the base point to maintain safe engine operating conditions. The resulting torque response of the

[3]In this case a cycle is defined as two revolutions of the crankshaft and has a measurement range from -360 to 360 CAD, where 0 CAD is equal to the top dead center after the compression phase.

[4]For example, with a CAN-Bus sampling rate of 10 ms and at an engine speed of 3000rpm, 360 data points from the AVL-Indismart occur during one sample of the CAN-Bus.

injection amount variation in steady state is as an example additionally depicted in Fig. 2.

A. *Extraction of information by principle component analysis*

To reduce the amount of data which is gathered during one combustion cycle, a principle component analysis (PCA) method is used to extract reliable features out of the cylinder pressure trace. PCA, also known as Karhunen-Loeve transform [7] projects the data onto a lower dimensional subspace in a way that the mean squared distance between the data points and their projection is minimized. To limit the influence of cyclic variations and disturbances for the next analysis the mean value over all 50 cycles was calculated for the pressure traces. The pressure matrix P is defined by aggregating the preprocessed pressure profiles characterizing the 29 different operating points (P is of the size 29×359). This matrix is now decomposed with the PCA in U, Σ and V. The indicated pressure matrix can be written as

$$P = U \Sigma V^T \quad (1)$$

$$PV = U \Sigma = p_{rec} \quad (2)$$

with Matrices V and U which are orthogonal: $UU^T = I, VV^T = I$. To obtain compact features (p_{rec}) it is necessary to multiply (1) with V. Now the pressure curve in P can be represented in coordinates of the orthonormal base vectors the so called Eigenpressures, see (2). These coordinates will now be used as inputs for model identification. As an example, the first four Eigenpressures are presented in the left part of Fig. 3.

Thanks to the used singular value decomposition, the according singular values are stored sorted to their relevance in the matrix Σ. To obtain information about the number of required base vectors to approximately reconstruct the original trace the singular values can be used. For a given number m of total singular values r with $m < r$ the error of the approximate reconstruction is bounded by

$$\epsilon_i = \sum_{i=m+1}^{r} \sigma_i^2. \quad (3)$$

As it can be seen in the right plot of Fig. 3, starting from σ_4 upwards the singular values are significantly smaller than the first one. This led to the assumption that a sufficient accuracy of the reconstruction can be achieved when four features are used. As an example the reconstructed trace for one of the recorded pressure traces is presented in Fig. 4. To this end, The pressure signal was reconstructed with (4) where u_k and v_k were appropriate orthogonal vectors similar to (2).

$$p = \sum_{k=1}^{4} \sigma_k u_k v_k^T \quad (4)$$

It should be mentioned that it is not possible or required to determine a direct physical relation between the features and the pressure trace, like it would be the case for e.g. CA50 or IMEP, because a black box modeling approach is pursued.

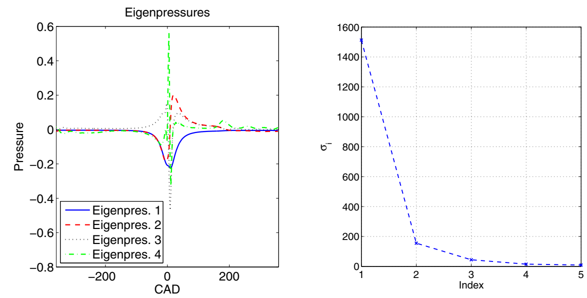

Fig. 3. Eigenpressure 1 - 4 and singular values

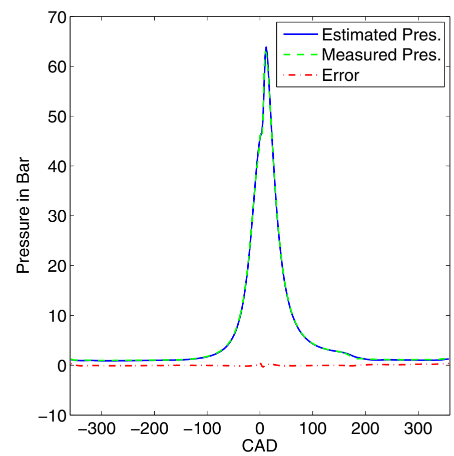

Fig. 4. Reconstructed pressure signal

B. *Engine torque model*

To determine a model of engine torque in dependency of the features a polynomial structure $f(u_k, \Theta)$, like in [9], was selected. One benefit of this structure is the linear relation in the parameters and thus it can be represented by the product of a parameter vector Θ with a data vector φ_k:

$$y_k = \varphi_k^T \Theta + e_k \quad (5)$$

Consequently, it is possible, under the assumption of an error e_k uncorrelated to $f(u_k, \Theta)$, to apply a standard least squares parameter estimation method and obtain an estimate $\hat{\Theta}$ of the parameter vector, [13]. So $\hat{\Theta}$ can be calculated with

$$\hat{\Theta} = (\Phi^T \Phi)^{-1} \Phi^T Y_{Torque}, \quad (6)$$

where Φ is the information matrix based on the inputs φ_k and Y_{Torque} is the data vector of the torque measurements.

For the described torque modeling, the PCA information was not used to reconstruct the pressure trace out of the feature values but in an opposite way, i.e. first the values of the four features $p_{rec1} \ldots p_{rec4}$ were determined (7).

$$p_{rec} = P_{29P} V_{29P} \quad (7)$$

where the index in P_{29P} and V_{29P} is corresponding to the 29 measured steady state points. Then, based on these features a second order polynomial model, see also [8], was parameterized to represent the engine torque. Initial analyzes showed that the inclusion of an additional input signal, namely the engine speed N substantially increased the model quality. So the overall torque model has a total number of 20 parameters assuming a 2^{nd} order polynomial function $f(u,\Theta)$ which have to be identified by the Least-Squares method and is presented in (8),

$$\begin{aligned} Y_{Torque} = \theta_1 p_{rec1} + \theta_2 p_{rec1} p_{rec1} + \theta_3 p_{rec1} p_{rec2} + \\ + \theta_4 p_{rec1} p_{rec3} + \theta_5 p_{rec1} p_{rec4} + \theta_6 p_{rec1} N + \\ + \theta_7 p_{rec2} + \theta_8 p_{rec2} p_{rec2} + \theta_9 p_{rec2} p_{rec3} + \theta_{10} p_{rec2} p_{rec4} + \\ + \theta_{11} p_{rec2} N + \theta_{12} p_{rec3} + \theta_{13} p_{rec3} p_{rec3} + \\ + \theta_{14} p_{rec3} p_{rec4} + \theta_{15} p_{rec3} N + \theta_{16} p_{rec4} + \theta_{17} p_{rec4} p_{rec4} + \\ + \theta_{18} p_{rec4} N + \theta_{19} N + \theta_{20} N N = \Phi^T_{Torque} \Theta_{Torque}. \end{aligned} \quad (8)$$

In addition, it should be noted that in general the relation between the features and the torque is a highly nonlinear function, as can be seen in Fig. 5 for the case of p_{rec3}. This fact is addressed by the polynomial structure of the model and in combination with the Least Squares method promising results were achieved. Notice that here the full order polynomial was used, where in the next local models a reduction of the necessary parameters was possible. In the particular case a reduction had dire effects on the model quality and was not applied. Fig. 6 shows the result of the identification. In addition also validation points from a different measurement data set were used to evaluate the performance outside of the identification dataset. Here it should be noticed that also these validation points were recorded only in stationary engine operating conditions. For the control approach two additional models are necessary which relate q_{MI} and φ_{MI} to the features. These two models have a similar structure and were identified based on separate measurements in selected operating points.

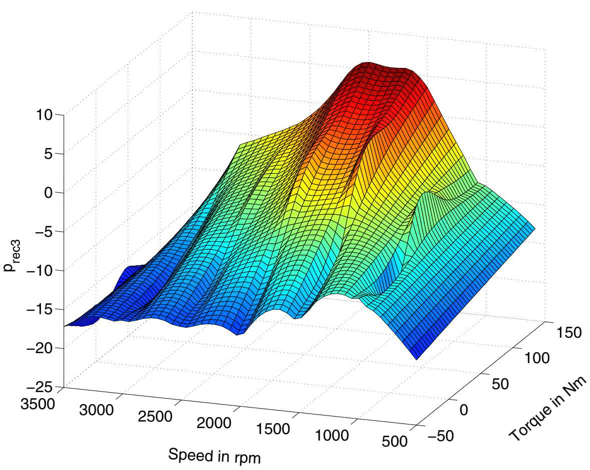

Fig. 5. p_{rec3} over torque and engine speed

C. Modeling main injection amount q_{MI}

The model of q_{MI} is determined by the variation of this quantity in three engine points which are also depicted in Fig. 2. Similar to torque model, also the features $p_{rec} = P_{qMI,var} V_{29P}$ for each point were calculated and again a polynomial approach was chosen. Here, an additional F-test was applied to determine the necessary polynomial inputs and led to the following reduced structure (9).

$$\begin{aligned} Y_{qMI} = \theta_1 p_{rec1} + \theta_2 p_{rec2} + \theta_3 p_{rec3} + \theta_4 p_{rec4} + \\ + \theta_5 p_{rec3} p_{rec3} = \Phi^T_{qMI} \Theta_{qMI} \end{aligned} \quad (9)$$

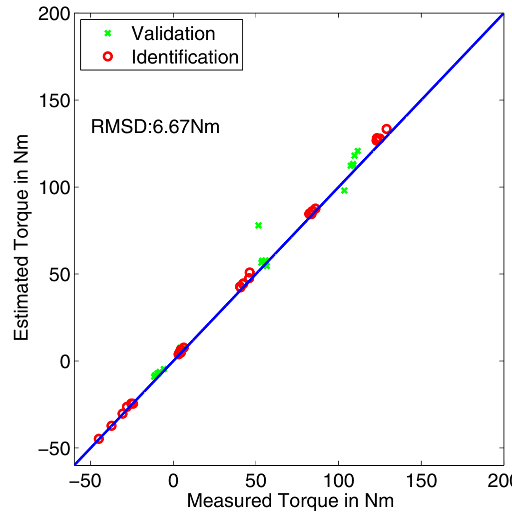

Fig. 6. Identification and validation of the torque model

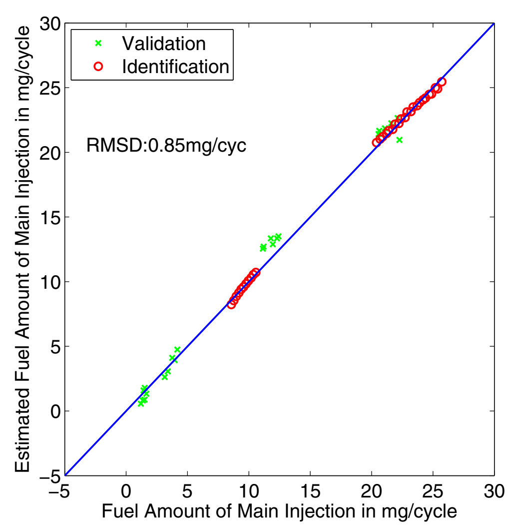

Fig. 7. Identification and validation p_{rec} - Main Injection Volume

D. Modeling Main Injection Angle φ_{MI}

Analog to the model for q_{MI} above again a variation measurement was performed in which φ_{MI} was varied in a close range around the base operating point. Again, first the assigned features were calculated with $p_{rec} = P_{\varphi_{MI,var}} V_{29P}$

and then a polynomial model was identified. Here also an F-test was performed and it turned out that a first order polynomial (10) was sufficient to model the relation between φ_{MI} and the features. However, it should be mentioned that this model is only valid in the identified engine operating points.

$$\begin{aligned} Y_{phiMI} &= \theta_1 p_{rec1} + \theta_2 p_{rec2} + \theta_3 p_{rec3} + \\ &\theta_4 p_{rec4} + \theta_5 N = \Phi^T_{\varphi_{MI}} \Theta_{\varphi_{MI}} \end{aligned} \quad (10)$$

Now all three identified submodels can be combined for the feature based control of the torque by q_{MI} and φ_{MI}.

IV. Torque control with Eigenpressures

The main target of this work is to control the engine torque over the compact features as intermediate quantity. The engine torque itself is closely related to the indicated mean effective pressure (IMEP) [5] and thus it was selected for a proof of concept of a feature based control. To this end a closed loop control structure, as depicted in Fig. 8, was implemented on the testbench system. As controlled inputs variable setpoints of features were used. Therefore a feed forward structure with an additional closed loop control was applied. The main task is focused at the *Indicated Pressure Control*, which calculates the control inputs q_{MI} and φ_{MI} from the features and engine speed, based on (10) and (9). Also an estimated engine torque is calculated for comparison but not used for direct torque feedback control. To close the control loop the deviation of every feature was compensated with an integral action with different weightings.

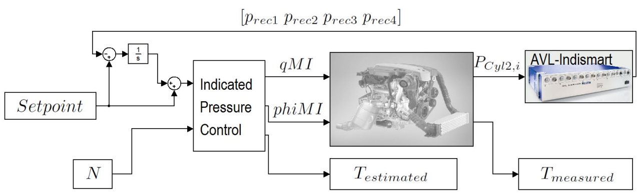

Fig. 8. Control loop of the indicated pressures

A. Online feature calculation

As already mentioned above, a real time transmission of a whole pressure trace over the CAN-Bus was not feasible. To circumvent this limitation the calculation of the features was done directly on the Indismart and then the values were sent via CAN to the dSpace System. The mathematical expression to determine the feature values is given in (11) whereupon the index i represents the actual indicated pressure.

$$p_{rec,i} = P_{Zyl,i} V_{29P} \quad (11)$$

B. Setpoint generation

Another, question is how to determine the setpoints for the features. Although, for the relation of desired engine torque and features a model was determined, it is not straightforward to obtain suitable references. One reason is the non uniqueness of the relation between features and inputs, moreover, due to the polynomial structure different feature combinations can lead to similar torque values. To circumvent this issue for the validation of the control feasible setpoints were derived from experimental data. To this end, the engine was operated at a constant engine speed of 1500 rpm and engine torque steps from 80 to 110 Nm with steps of 5 Nm were performed and the corresponding feature values recorded.

C. Experimental results

In Fig. 9 the obtained experimental results of the feature based torque control are depicted. In this experiment the engine was first set to a standard operating point inside the range of the setpoints, namely at 100 Nm and afterwards the control was switched on with the first setpoint at $T_{des} = 80$ Nm. The control strategy adapts the main injection and thus tracks the desired torque value which is determined by the feature set. This was done only by the feedback of the feature values and neither by a measured torque feedback or a feedback of the virtual sensor. The results of the virtual torque sensor, based on the features are also depicted in this figure, to show the accuracy of the feature based engine torque estimation outside of standard operating conditions[5]. The control result for the four features is presented in Fig. 10.

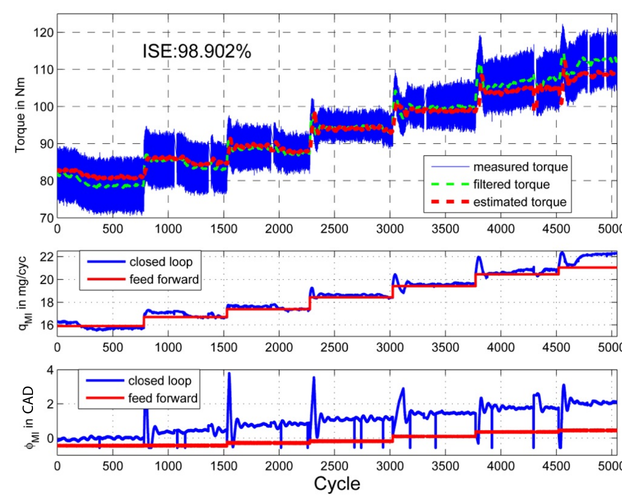

Fig. 9. Performance evaluation of the feature based control

Here it can be seen that even with the integral action it was not possible to control all four features to their desired setpoints. However, the measured torque corresponds in the region of the initial operating point well with the desired torque during the determination of the setpoints and also with the estimated torque based on the features.

D. Discussion

As can be seen in the experimental results of the feature tracking control it was not possible to directly control all four features which led to deviations from their setpoints but still the torque was controlled to the desired range. Still, it

[5]The identification dataset for the torque model did not cover this particular operating region, in view of changes on the main injection fuel amount and also the angle of main injection.

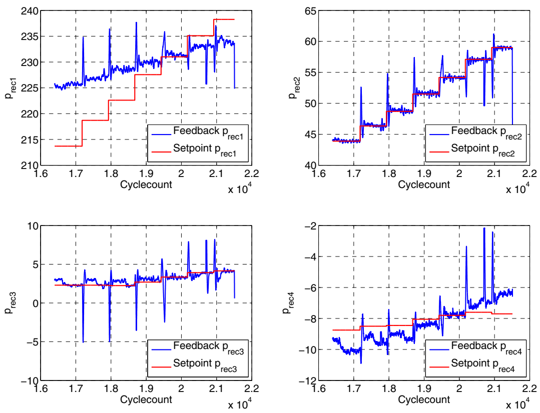

Fig. 10. Results for the feature control at 1500rpm

should be noted that for example in p_{rec1} the deviation is less then 2.5% and it was possible to control p_{rec2} and p_{rec3} close to the desired setpoints. One possible explanation for the different tracking results can be the fact that the pressure trace which is the foundation for the feature values is not only depending on the considered inputs but also on other influences, like the air system states. For example, the boost and exhaust pressure have a high influence on the in-cylinder pressure trace. Although these pressures are coupled with the injected fuel amount other actuators, like EGR valves or turbine guide vanes, which cannot be altered by the injection system have a high control authority on them. This can be seen as reason why the feature tracking was almost perfect in the region of approximately $100\,\mathrm{Nm}$ because this was the original setpoint for the air-system[6]. Further it should be noted that in this application only 2 control inputs were considered and in total four different quantities should be controlled to their setpoints. As it can be recognized from the identified models both inputs have an influence on all four features and thus it is not possible to control them independently.

V. Conclusions

In this work a different approach to a cylinder pressure based engine control was presented, where the essential information of the pressure trace was extracted PCA methodology. This approach is different to the state of the art, where typically physical related quantities are used for control feedback. Based on the extracted features different models for control design were determined and afterwards used for an engine torque control. The control was applied on a real engine and led to first satisfactory results. However, due to the non bijective relation between the torque and the features and the number and type of considered control inputs it was not possible to directly determine the desired features based on the models.

In the next steps it should be investigated if a different approach relating features and additional physical quantities could lead to convincing results or if a combination of several feature based models can be used to obtain a set of desired and distinct feature setpoints. Here a possible method can be the combination of torque, NO_x and PM emissions models to design a feasible set of desired features by imposing conditions on the relation between them. In this case also the air system and so additional control inputs should be taken into account. Finally, it should be mentioned that it was possible to reconstruct engine torque with high accuracy from the features and so a different approach could be the use of a virtual torque sensor for control feedback instead of the feature based control.

[6]Notice that the air-system inputs were kept at fixed conditions during the experiment.

VI. Acknowledgments

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