2011 50th IEEE Conference on Decision and Control and
European Control Conference (CDC-ECC)
Orlando, FL, USA, December 12-15, 2011

A Hybrid Control Approach for Low Temperature Combustion Engine Control

T. Albin, P. Drews, F. Heßeler, A. M. Ivanescu, T. Seidl and D. Abel

Abstract— **In this paper, a hybrid control approach for low temperature combustion engines is presented. The identification as well as the controller design are demonstrated. In order to identify piecewise affine models, we propose to use correlation clustering algorithms, which are developed and used in the field of data mining. We outline the identification of the low temperature combustion engine from measurement data based on correlation clustering. The output of the identified model reproduces the measurement data of the engine very well. Based on this piecewise affine model of the process, a hybrid model predictive controller is considered. It can be shown that the hybrid contoller is able to produce better control results than a model predictive controller using a single linear model. The main advantage is that the hybrid controller is able to manage the system characteristics of different operating points for each prediction step.**

I. INTRODUCTION

A. Low temperature combustion engines

One of the most important recent topics in the automotive industry is the development of vehicles with clean and efficient drives. Increased fuel prices on the one side and an increased awareness for environmental pollution on the other side are reasons for focussing on this topic. The politics is enforcing the development of clean and efficient drives by laws, like the EURO 6 in Europe. The EURO 6 Norm is setting limits on nitrogen oxides (NO_X), carbon monoxides (CO), unburned hydrocarbons (HC) and particulate matter (PM). Thus, a strong focus of recent research is put on improving efficiency and reducing CO_2 in internal combustion engines (ICE), while maintaining strict limitations on pollutant emissions. The simultaneous reduction of those emissions is to some extend a contradictionary task, which can not be satisfied with conventional combustion processes. A promising technology to reach these goals are engines with low temperature combustion (LTC).

LTC engines can be operated with gasoline, which is often called Controlled Auto Ignition (CAI) or with Diesel, often called Homogeneous Charge Compression Ignition (HCCI) or Partial Homogeneous Charge Compression Ignition (PCCI) depending on the degree of homogenisation of the air/fuel mixture. In [1] a good overview of the LTC combustion process is given. CAI and PCCI/HCCI are both characterized by higher exhaust gas recirculation rates (EGR) and higher homogenisation compared to conventional combustion processes. This leads to a lower peak temperature in combustion, which results in reduced NO_X-emissions. Moreover, these characteristics lead to a fast conversion of the fuel as self ignition occurs simultaneously at several places in the combustion chamber. The fast conversion of fuel is beneficial for high efficiency. In [2] it is reported that for LTC engines NO_X can be reduced by 90 - 99% and fuel consumption by approx. 15%.

B. Control of low temperature combustion engines

With the introduction of this new combustion process several challenges arise, which make it a recent object of research. The LTC combustion process shows a highly nonlinear process behavior and is very sensitive to a high number of influencing factors, like the inlet air temperature [1]. For operating the engine in this combustion mode, a process control is necessary, which allows for reference tracking and rejection of disturbances. Some control approaches exist, where the controllability of the LTC combustion is shown, as in [3].

Due to physical limitations of the LTC combustion process, it can only be used for low to medium speed and load [2] of the engine. For the use in a car, the engine has to be operated in both, the conventional and the LTC mode. The changeover in the input signals between these combustion modes is smooth. Depending on the grade of homogenisation and EGR rate the system characteristics change. In order to deliver the requested torque of the driver, with minimal fuel consumption and pollutant emissions, the process control has to manage the whole operating range of the engine. Instead of logic based switching between the modes, a hybrid control approach is investigated in this paper. A hybrid controller is systematically able to decide in which mode to operate. In particular we investigate the hybrid model predictive control (MPC) because this gives us the possibility to be optimal with respect to a cost function, which allows to penalize e.g. the fuel consumption and to consider actuator limitations. The hybrid MPC has proven satisfactory e.g. for direct injection stratified engines [4].

In this paper we apply the hybrid MPC approach to a PCCI Diesel engine. We outline the whole process from identification to the control of the PCCI engine. The paper is organized

The authors gratefully acknowledge the contribution of the Collaborative Research Center 686 'Model-based control of homogenized low-temperature combustion' supported by the German Research Foundation (DFG) at RWTH Aachen University, Germany, and Bielefeld University, Germany, see www.sfb686.rwth-aachen.de for details.

T. Albin, P. Drews, F. Heßeler and D. Abel are with the Institute of Automatic Control, Department of Mechanical Engineering, RWTH Aachen University, 52074 Aachen, Germany {T.Albin, P.Drews, F.Hesseler, D.Abel}@irt.rwth-aachen.de

A. M. Ivanescu and T. Seidl are with the Department for Computer Science 9 (Data Management and Data Exploration), RWTH Aachen University, 52072 Aachen, Germany {ivanescu,seidl}@cs.rwth-aachen.de

as follows: After demonstrating the control problem for the PCCI process, we propose correlation clustering algorithms for the identification of piecewise affine (PWA) models. We employ one of the existing correlation clustering algorithms in order to identify a PWA model. Based on this PWA model the hybrid MPC controller is presented. Finally we show simulation results of the hybrid MPC and compare it to a constrained MPC based on a linear model.

II. Problem Setup

The control problem for LTC engines is studied in this paper for a Diesel engine. A modern 1.9l four cylinder Diesel engine with classical EGR air path structure and variable geometry turbine (VGT) is used at a test bench. Further remarks on the used engine can be found in [5]. We denote the controlled outputs as $\mathbf{Y} \in \mathbb{R}^3$. The main task of the process control is to deliver the requested torque of the driver. As the indicated mean effective pressure Y_{IMEP} correlates to the delivered torque, Y_{IMEP} is used as first controlled output. In order to estimate the characteristics of the combustion process, e.g. concerning the combustion efficiency, the position of the combustion average Y_{CA50} after top dead center is used as second controlled output. As third controlled output, we consider the maximum cylinder pressure gradient Y_{dPmax}, which correlates to the noise emissions. All three outputs can be determined by evaluation of the cylinder pressure signal from the engine.

$$\mathbf{Y} = \begin{bmatrix} Y_{IMEP} \\ Y_{CA50} \\ Y_{dPmax} \end{bmatrix} \quad \mathbf{U} = \begin{bmatrix} U_{FMI} \\ U_{SOI} \\ U_{EGR} \end{bmatrix} \tag{1}$$

The actuated variables are denoted as $\mathbf{U} \in \mathbb{R}^3$. To manipulate the fuel injection, we use a common rail Diesel injector, where we can set the amount of injected fuel mass U_{FMI} and the start of injection after top dead center U_{SOI}. The third actuated variable is the EGR rate U_{EGR}, defined as: $U_{EGR} = \frac{\dot{M}_{EGR}}{\dot{M}_{EGR}+\dot{M}_{AIR}}$, where $\dot{M}_{EGR}$ is the recirculated exhaust gas mass flow and $\dot{M}_{AIR}$ is the mass flow of fresh air. All three control inputs have an influence on all three outputs, thus resulting in a coupled multiple input multiple output control problem, see (1).

III. Piecewise Affine System Identifaction

A. Correlation Clustering

In this chapter we examine the system identification of PWA models. For the identification of PWA models, we introduce corellation clustering algorithms. Based on this, we apply the corellation clustering to the steady state measurement data of the Diesel engine. In the following we consider PWA models of the form:

$$\mathbf{X}(k+1) = \mathbf{A}^{i(k)} \cdot \mathbf{X}(k) + \mathbf{B}^{i(k)} \cdot \mathbf{U}(k) + \mathbf{f}^{i(k)} \tag{2}$$

$$\mathbf{Y}(k) = \mathbf{C}^{i(k)} \cdot \mathbf{X}(k) + \mathbf{g}^{i(k)} \tag{3}$$

$$i(k) \;\; s.t. \;\; \mathbf{H}^{i(k)} \cdot \mathbf{X}(k) + \mathbf{W}^{i(k)} \cdot \mathbf{U}(k) \leq \mathbf{K}^{i(k)} \tag{4}$$

Hereby $\mathbf{X} \in \mathbb{R}^n$ denotes the state vector at the discrete time $k \in \{1, 2, 3, ..\}$, $i(k) \in \{1, ..., s\}$ denotes the current mode of the hybrid system, with s being the number of modes. $\mathbf{A}^{i(k)}$, $\mathbf{B}^{i(k)}$, $\mathbf{C}^{i(k)}$, $\mathbf{f}^{i(k)}$, $\mathbf{g}^{i(k)}$ are constant matrices describing the affine models. The constant matrices $\mathbf{H}^{i(k)}$, $\mathbf{W}^{i(k)}$ and $\mathbf{K}^{i(k)}$ from the linear inequalities in (4) describe the boundaries, called guardlines, in which the different affine models are active. If the parameters for the affine models and the guardlines are not known, different techniques are available for identification. One way is to use clustering based identification techniques. In this case the following three steps are carried out. First, the data set is partioned into s clusters. Second, the input data space is divided into s partitions according to the clusters in order to compute the parameters for the guardlines $\mathbf{H}^{i(k)}$, $\mathbf{W}^{i(k)}$ and $\mathbf{K}^{i(k)}$. Third, a standard identification technique, like the regression analysis, can be used to identify the model for each partition. Different clustering algorithms can be employed for the first step of the identification, such as proposed in [6] and [7]. Traditional clustering algorithms, like k-means, group points based on their spatial proximity and do not take linear correlations into consideration. Beside these algorithms also correlation clustering algorithms were developed and applied in the field of data mining, like [8], [9] and [10]. Compared to traditional clustering algorithms, the correlation clustering algorithms are better suited for the task of PWA model identification as they group points based on their correlation. For the example given in Fig. 1, the traditional k-means clustering algorithm partitions the data in such a way, that all the points are closest to the centroid of the own cluster, see Fig. 1.a. Correlation clustering algorithms divide the points such that each cluster is described by a linear equation of a hyperplane yielding the two clusters from Fig. 1.b.

The correlation clustering algorithms are based on the principal component analysis (PCA), which is able to detect correlations between dimensions. We assume $\mathcal{S}$ to be a set of d-dimensional points, i.e. $\mathcal{S} \subseteq \mathbb{R}^d$, and let $\overline{\mathbf{p}} \in \mathbb{R}^d$ denote the algebraic average of all points $\mathbf{p} \in \mathcal{S}$. The *covariance matrix* $\mathbf{\Sigma}_{\mathcal{S}} \in \mathbb{R}^{d \times d}$ of $\mathcal{S}$ is defined as:

$$\mathbf{\Sigma}_{\mathcal{S}} = \frac{1}{|\mathcal{S}|} \sum_{\mathbf{p} \in \mathcal{S}} (\mathbf{p} - \overline{\mathbf{p}}) \cdot (\mathbf{p} - \overline{\mathbf{p}})^T \tag{5}$$

Since the clusters are identified by employing the PCA and not based on regression analysis, correlation clustering algorithms do not distinguish between input and output dimensions. This allows us to consider the input and output dimensions together in the clustering step. Thus we compute the clustering in a d dimensional space, where d results from the sum of input and output dimensions and use the outcome to partition the input space. Based on the partitioning a PWA model can be build. The PCA decomposes $\mathbf{\Sigma}_{\mathcal{S}}$ into an eigenvector matrix $\mathbf{V}$ and a diagonal matrix $\mathbf{E}$ containing the eigenvalues: $\mathbf{\Sigma}_{\mathcal{S}} = \mathbf{V} \cdot \mathbf{E} \cdot \mathbf{V}^T$. The eigenvectors span a new coordinate system. $\mathbf{E}$ is the covariance matrix of the points in $\mathcal{S}$, when represented in this new coordinate system, the eigenvalues represent the variances along the new axes. If the points are linearly dependent, one or more eigenvalues will be close to zero. The eigenvectors corresponding to the

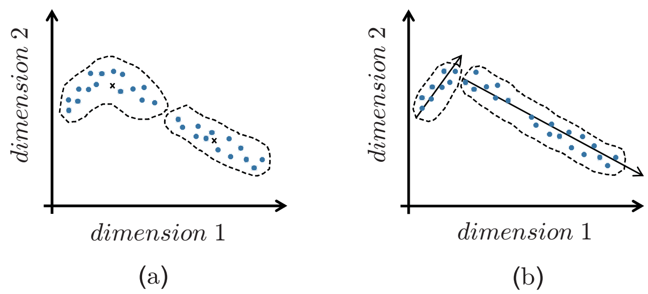

Fig. 1. k-means (a) versus correlation (b) clustering

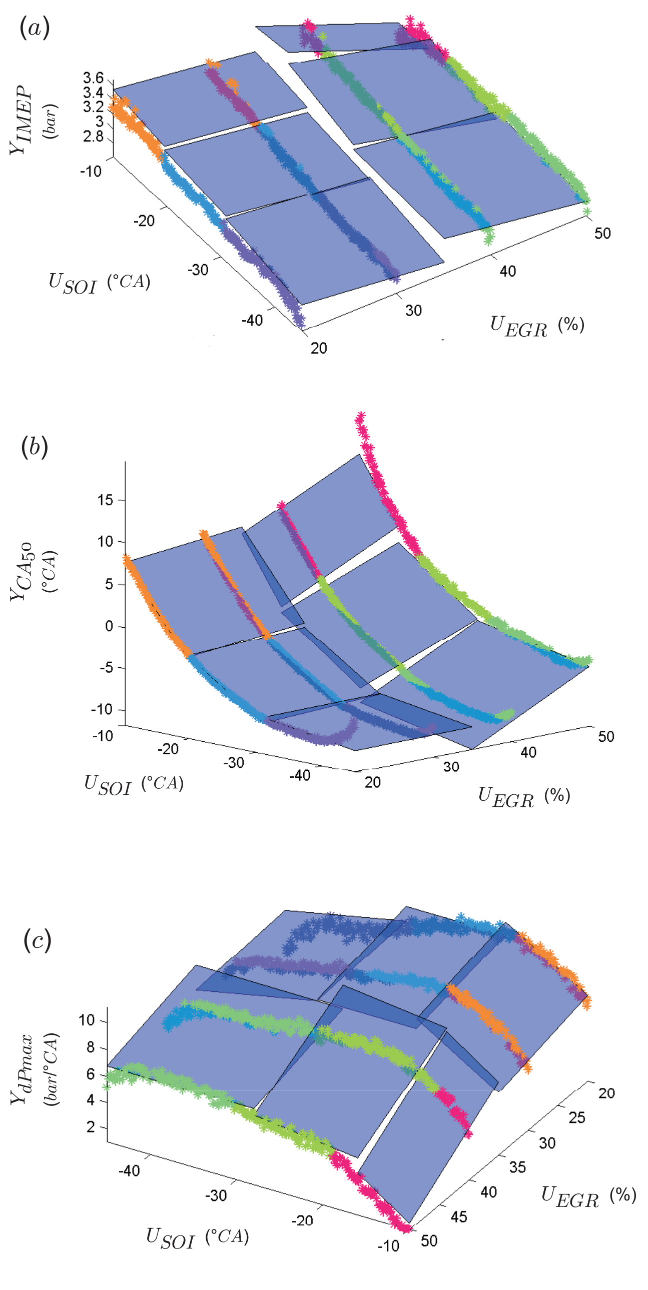

Fig. 2. Steady state measurement data along with the steady state model output from the identified PWA model for (a) Y_{IMEP} (b) Y_{CA50} (c) Y_{dPmax}

dominating eigenvalues define the hyperplane approximating the data.

For the construction of PWA models, we use the $ORCLUS$ algorithm [9], which is a correlation clustering algorithm that allows the user to specify the desired number of clusters. $ORCLUS$ also makes use of the PCA to identify a new coordinate system in which the correlation between the dimensions is minimized. By leaving out the eigenvectors with a low corresponding eigenvalue, we obtain a set of eigenvectors which best describe the data. Let $\mathcal{E} = \{\mathbf{e_1}, ..., \mathbf{e}_\delta\}$ be a set of $\delta \leq d$ orthonormal vectors in the d-dimensional space, which define a subspace. The projection of a point $\mathbf{p} \in \mathcal{S}$ in subspace $\mathcal{E}$ is a δ-dimensional point $\mathcal{P}(\mathbf{p}, \mathcal{E}) = (\mathbf{p} \cdot \mathbf{e_1}, ..., \mathbf{e_p} \cdot \mathbf{e}_\delta)$.

The projected energy $\mathcal{R}(\mathcal{S}, \mathcal{E})$ of $\mathcal{S}$ in the subspace $\mathcal{E}$ is defined as the sum of distances of the points to the centroid:

$$\mathcal{R}(\mathcal{S}, \mathcal{E}) = \frac{1}{|\mathcal{S}|} \sum_{\mathbf{p} \in \mathcal{S}} \|\mathcal{P}(\mathbf{p}, \mathcal{E}) - \mathcal{P}(\overline{\mathbf{p}}, \mathcal{E}))\|_2 \quad (6)$$

The diagonalization of the covariance matrix computed by the PCA provides the necessary information about the coordinate systems, which minimize the projected energy, by picking the eigenvectors with the smallest eigenvalues.

Since the points in a dataset are usually described by more than one hyperplane, the PCA on the whole dataset would yield a high projected energy. Hence to identify several hyperplanes the PCA is performed locally. $ORCLUS$ is a buttom up hierarchcal algorithm. It starts with a set of clusters, each containing one point:

$$\mathcal{S}^{(0)} = \{\{\mathbf{p_1}\}, \{\mathbf{p_2}\}, ..., \{\mathbf{p}_{|\mathcal{S}|}\}\} \quad (7)$$

and incrementally merges them such that the resulting clusters have a low projected energy. In the l-th iteration $\mathcal{S}^{(l)}$ becomes $\mathcal{S}^{(l+1)}$ by merging the pair with minimal energy:

$$(i, j) = \underset{\substack{(i,j) \\ \mathcal{S}_i, \mathcal{S}_j \in \mathcal{S}^{(l)}}}{\arg\min}\ \mathcal{R}(\mathcal{S}_i \cup \mathcal{S}_j, \mathcal{E}_{\mathcal{S}_i \cup \mathcal{S}_j}) \quad (8)$$

The resulting clustering is:

$$\mathcal{S}^{(l+1)} = \mathcal{S}^{(l)} - \{\mathcal{S}_i, \mathcal{S}_j\} \cup \{\mathcal{S}_i \cup \mathcal{S}_j\} \quad (9)$$

The $ORCLUS$ algorithm merges two clusters if their least spread directions are similar, hence the points are likely to be located on a similar plane and the clusters are merged. This step is repeated until the desired number of clusters is reached.

B. Identification of a hybrid model for the PCCI engine

In order to identify a model of the PCCI engine we have conducted measurements on a real engine test bench at a constant speed of 2000 rpm. The measurements show a highly nonlinear behavior of the process concerning the steady state relationship between in- and outputs, see Fig. 2. In order to reduce model complexity, it is reasonable to describe the model in a Wiener-type dynamics, see [11]. The model consists of a series connection of a linear dynamic term and a nonlinear static term. We determine the linear dynamic term as described in [11], independently from the operating point, by system identification. This yields to a constant matrix $\mathbf{A}^{i(k)} \equiv \mathbf{A}$ in our PWA model approach. In order to obtain $\mathbf{X}(k) = \mathbf{U}(k)$ in steady state, we set $\mathbf{B}^{i(k)} = (\mathbf{I} - \mathbf{A})$, $\mathbf{g}^{i(k)} \equiv 0$, with $\mathbf{I}$ being the identity matrix. On top of that, we set $\mathbf{W}^{i(k)} \equiv 0$. Based on this choice, we can reproduce the nonlinear part, as it is assumed static, by identifying the matrices $\mathbf{H}^i$, $\mathbf{K}^i$, $\mathbf{C}^i$ and $\mathbf{f}^i$. These matrices are computed by deploying the presented $ORCLUS$ algorithm.

Fig. 2 illustrates the results from the PWA model identification with $ORCLUS$. The 6-dimensional steady state data points with input dimension 3 and output dimension 3 were partitioned into 6 clusters. The different colors of the measurement data in the figures indicate in which cluster the datapoints were grouped in the clustering step. The obtained partitioning of the 3-dimensional input space was used to construct a PWA model by employing the regression analysis. In the figures the steady state outputs of the PWA model in the different hyperplanes, defined by the guardlines, are depicted. For the 3D visualization we chose the points with $U_{FMI} = 12.5$ mm^3/cycle and plotted the inputs U_{SOI} and U_{EGR} over the steady state outputs Y_{IMEP} in Fig. 2.a, Y_{CA50} in Fig. 2.b and Y_{dPmax} in Fig. 2.c. The results show, that the correlation clustering algorithm is capable of identifying the areas with different system behavior. With the affine models in the different modes, the measurement data can be reproduced very well.

IV. Hybrid Model Predictive control

In the MPC framework, a model is used to predict the controlled outputs of the plant over a finite time horizon H_p. Based on this prediction, a finite horizon open-loop optimization problem is solved. By minimizing a given cost function subject to constraints, the MPC algorithm computes an optimal control sequence $\Delta\mathbf{U}^* = \Delta\mathbf{U}^*_{(k|k)} .... \Delta\mathbf{U}^*_{(k+H_u-1|k)}$ for the control horizon H_u, at the discrete time instant k with $k \in 0, 1, 2, ...$, where $(\cdot)_{(k+j|k)}$ denotes the prediction of the variable $(\cdot)$ for the time instant $k + j$ at time k. After optimization only the first control signals $\mathbf{U}(k)$ are applied to the system, where $\mathbf{U}(k) = \mathbf{U}(k-1) + \Delta\mathbf{U}^*_{(k|k)}$. The optimization problem is solved in each time step: at the next time step a new optimization is solved over a shifted prediction horizon. This procedure realizes a feedback mechanism, which makes reference tracking and disturbance rejection possible [12].

In the cost function deviations of the controlled outputs from the reference values $\mathbf{Y}_{ref}$ are pruned as well as changes of actuator signals $\Delta\mathbf{U}$ and the absolute value of the actuator signal U_{FMI}. We use a quadratic norm in the cost function:

$$J = \sum_{j=1}^{H_p} \left[(\mathbf{Y}_{(k+j|k)} - \mathbf{Y}_{ref})^T \cdot \mathbf{Q} \cdot (\mathbf{Y}_{(k+j|k)} - \mathbf{Y}_{ref}) \right] + \sum_{j=0}^{H_u-1} \left[(\Delta\mathbf{U}^T_{(k+j|k)} \cdot \mathbf{R} \cdot \Delta\mathbf{U}_{(k+j|k)}) + U_{FMI(k+j|k)} \cdot S_{FMI} \cdot U_{FMI(k+j|k)} \right] \quad (10)$$

With the variable S_{FMI} we are able to penalize the fuel consumption. As the absolute value of U_{EGR} and U_{SOI} are nonrelevant, they are not considered in the cost function. With the $\mathbf{Q}$ and $\mathbf{R}$ matrices it is possible to tune the controller in order to weight the control error as well as the changes in the control input. They are defined as follows:

$$\mathbf{Q} = \begin{pmatrix} Q_{IMEP} & 0 & 0 \\ 0 & Q_{CA50} & 0 \\ 0 & 0 & Q_{dP_{max}} \end{pmatrix}, \quad (11)$$

$$\mathbf{R} = \begin{pmatrix} R_{FMI} & 0 & 0 \\ 0 & R_{SOI} & 0 \\ 0 & 0 & R_{EGR} \end{pmatrix} \quad (12)$$

In the case of hybrid MPC, the evaluation of the cost function is based on a hybrid model. The hybrid model can be described, among others, by a mixed logical dynamical (MLD) model or a PWA model [13]. For PWA models the following optimization problem has to be solved, in order to determine the control input that is applied to the plant at the next time instant:

$$\min_{\Delta\mathbf{U}} J \quad (13)$$

subject to:

$$\begin{aligned}
&\mathbf{X}_{(k+j+1|k)} = \mathbf{A}^{i(k+j)} \cdot \mathbf{X}_{(k+j|k)} + \mathbf{B}^{i(k+j)} \cdot \mathbf{U}_{(k+j|k)} + \mathbf{f}^{i(k+j)}, && j = 0, ..., H_p - 1 \\
&\mathbf{Y}_{(k+j|k)} = \mathbf{C}^{i(k+j)} \cdot \mathbf{X}_{(k+j|k)} + \mathbf{g}^{i(k+j)} + \mathbf{P} \cdot \epsilon_{(k+j|k)}, && j = 1, ..., H_p \\
&i(k+j) \;\; s.t. \;\; \mathbf{H}^{i(k+j)} \cdot \mathbf{X}_{(k+j|k)} \leq \mathbf{K}^{i(k+j)}, && j = 0, ..., H_p - 1 \\
&\mathbf{U}_{Min} \leq \mathbf{U}_{(k+j|k)} \leq \mathbf{U}_{Max}, && j = 0, ..., H_p - 1 \\
&\epsilon_{(k+j|k)} = \epsilon(k), && j = 1, ..., H_p
\end{aligned}$$

where J denotes the cost function, which has to be minimized and $\mathbf{P}$ a constant matrix. $\mathbf{U}_{Min}$ and $\mathbf{U}_{Max}$ are the absolute constraints for the control inputs $\mathbf{U}(k)$. The values correspond to the physical limitations of the actuators. In order to account for mismatch between the internal controller model and the real world behavior, integrating behaviour is added to the system by introducing $\epsilon(k)$, which gives an alignment between the model prediction $\mathbf{Y}_{(k|k-1)}$ and the measured value $\tilde{\mathbf{Y}}(k)$ and is assumed to be constant over the prediction horizon.

There are different ways to solve the optimization problem stated in (13). One possible way is to translate the given PWA model into a Mixed Logical Dynamical (MLD) system, as stated in [14]. The resulting optimization problem can be cast into a mixed integer quadratic program (MIQP) and then solved offline to obtain an explicit controller [15]. But as the focus in this paper is not on calculation efficiency, but more on exploiting the structure of the hybrid MPC needed for the examined PCCI engine, we solve the evolving optimization problem online. This gives us the possibility to test different control settings quickly. We determine all feasible switching sequences v_r [16]. In our case the guardlines of the PWA model are clustered only concerning the state variables, which leads to $r \in \{1, ..., s^{H_p}\}$ possible switching sequences. For each switching sequence v_r, one finite-time optimal control (FTOC) problem J_r results as in the standard linear constrained MPC case [12]:

$$\min_{\Delta \mathbf{U}} J_r, \text{ with } i(k) = v_r \quad (14)$$

The overall minimizer J^* of the problem stated in (13) results from comparing the s^{Hp} FTOC problems:

$$J^* = min\{J_1^*, ..., J_{s^{H_p}}^*\} \quad (15)$$

The control sequence minimizing the s^{H_p} FTOC problems is equal to the control sequence $\Delta\mathbf{U}^*$ minimizing the original cost function J. As the reduced optimization problems are standard FTOC problems, well known Quadratic Programming (QP) solving techniques can be used.

V. Simulation Results

In the following, the simulation results for the hybrid control approach of the PCCI combustion process for constant engine speed of 2000 rpm are demonstrated. The hybrid controller, as proposed in section 4, is compared to a constrained linear MPC. The only difference between the two controllers is that the linear MPC is based on a single linear model. MATLAB/Simulink™ was used for the implementation of the controllers and quadprog as QP-Solver. We have used a Wiener-type dynamics for the plant model in the simulations. The plant model consists of a series connection of linear dynamic transfer functions and a nonlinear Neural Network. The Neural Network is in the type of a Feed-forward backpropagation with two layers, sigmoid activation functions and 20 neurons. The model is capable to reproduce the engine behaviour in a highly accurate manner, see [5]. In the simulations we have superposed the output of the Neural Network with random noise. Both controllers use the same $\mathbf{Q}$ and $\mathbf{R}$ matrices and S_{FMI}. The values for the weighting matrices were set according to the importance of the affected parameter for the control task. E.g. in the controller the value Q_{IMEP} for tracking the IMEP value is weighted high, as this is a very important task. The presented control results were achieved with following values:

$$Q_{IMEP} = 100, \quad Q_{CA50} = 10, \quad Q_{dPmax} = 0.3 \quad (16)$$

In the cost function (10) it is also possible to consider deviations of the actuator signal. Here we prune especially the deviations of U_{EGR} as the EGR-rate can only slowly be changed.

$$R_{SOI} = 0.05, \quad R_{EGR} = 0.3, \quad R_{FMI} = 0.1 \quad (17)$$

In the cost function (10) we also consider the absolute value of U_{FMI} in order to get a fuel efficient controller:

$$S_{FMI} = 0.1 \quad (18)$$

The constraints on the actuated signals are set according to the actuator limitations and stability issues of the engine:

$$\begin{bmatrix} 10 \\ 20 \\ -50 \end{bmatrix} \leq \begin{bmatrix} U_{FMI} \\ U_{EGR} \\ U_{SOI} \end{bmatrix} \leq \begin{bmatrix} 20 \\ 50 \\ -10 \end{bmatrix} \quad \begin{pmatrix} mm^3/cycle \\ \% \\ ^\circ CA \end{pmatrix} \quad (19)$$

TABLE I
Comparison between Hybrid MPC and Linear MPC

	Hybrid MPC	Linear MPC
RMS Y_{IMEP} (bar)	0.1	0.1
RMS Y_{CA50} (° CA)	1.1	2.0
RMS Y_{dPmax} (bar/°CA)	2.3	2.1
Avg. Y_{IMEP} (bar)	3.1	3.1
Avg. U_{FMI} (mm^3/cycle)	12.2	12.6

In the optimization problem we have used $H_P = 2$, $H_U = 2$, $\mathbf{P} = \mathbf{I}$ and the sampling time was chosen to $T_S = 0.06s$. The states $\mathbf{X}(k)$ and $\epsilon(k)$ are determined by an extended Kalman-Filter. The Kalman-Filter uses the same model as the Hybrid respectively linear MPC algorithm. As setpoints for $Y_{IMEP,ref}$ and $Y_{CA50,ref}$ we use ramps and steps. Due to the physical coupling of Y_{dPmax} to the other controlled outputs, the three outputs can not be controlled independently without offset. Thus we set the setpoint constant to a low value of $Y_{dPmax,ref} = 6$ bar/°CA, which allows the controller to track Y_{CA50} and Y_{IMEP}, while trying to minimize Y_{dPmax} to a reasonable value.

For the hybrid MPC, the model identified in section 3 is used. The presented results for the linear constrained MPC controller use one of the six models from the PWA model. We have also tested the closed loop simulations with different other linear models for the linear controller, but they lead to comparable results. In Table I the root mean square (RMS) is compared for the two controllers. In Fig. 3 the simulation results for the controlled ouputs are shown and in Fig. 4 the corresponding actuated variables.

The proposed hybrid controller is able to track $Y_{IMEP,ref}$ and $Y_{CA50,ref}$ during the whole simulation time very well, while Y_{dPmax} is held at a reasonably low level. The linear constrained MPC is also able to track $Y_{IMEP,ref}$ very well. In contrast, $Y_{CA50,ref}$ is not tracked as good as in the hybrid MPC case. The RMS error of Y_{dPmax} is comparable for both controllers. But one can see that Y_{dPmax} is very unsteady for the linear case.

The acutated variables of the two controllers differ a lot, the linear MPC e.g. only sets low values on the EGR rate U_{EGR}. As the hybrid controller is aware of the different operating point dependent dynamic charasterics, it is able to take the nonlinearities into account and achieve much better control results. At $t = 15.1sec$ for example the hybrid controller is performing a mode switch from the conventional to the PCCI region with an earlier time of injection in U_{SOI}. The linear controller is not aware of the nonlinearities and thus the boundaries of U_{SOI} and U_{EGR} are reached.

As can be seen in Table I, the average Y_{IMEP} is same for both controllers. Nevertheless with the hybrid controller 3% less fuel consumption is needed for the same average load. The hybrid controller is able to optimize over the entire operating area for a fuel minimizing control variable. As conclusion it can be said, that the hybrid control approach is suited very well for the control of the PCCI engine.

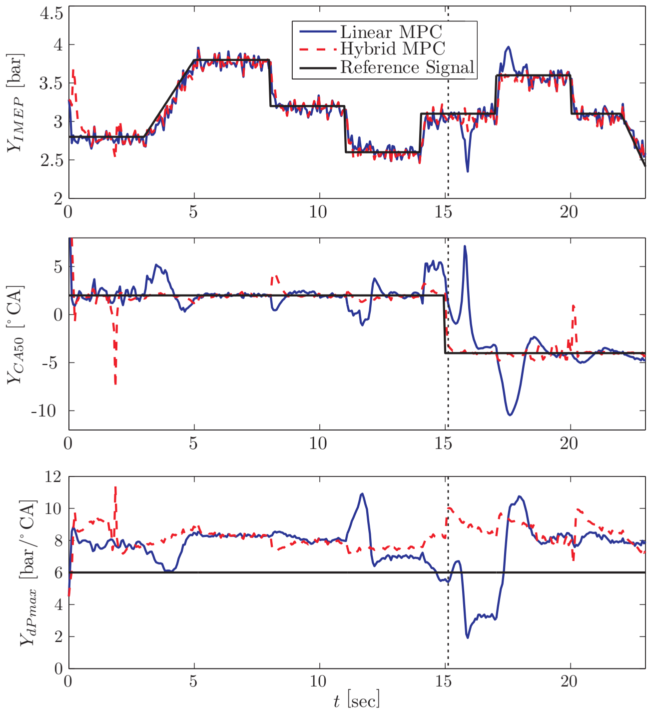

Fig. 3. Closed Loop Result: Controlled variables

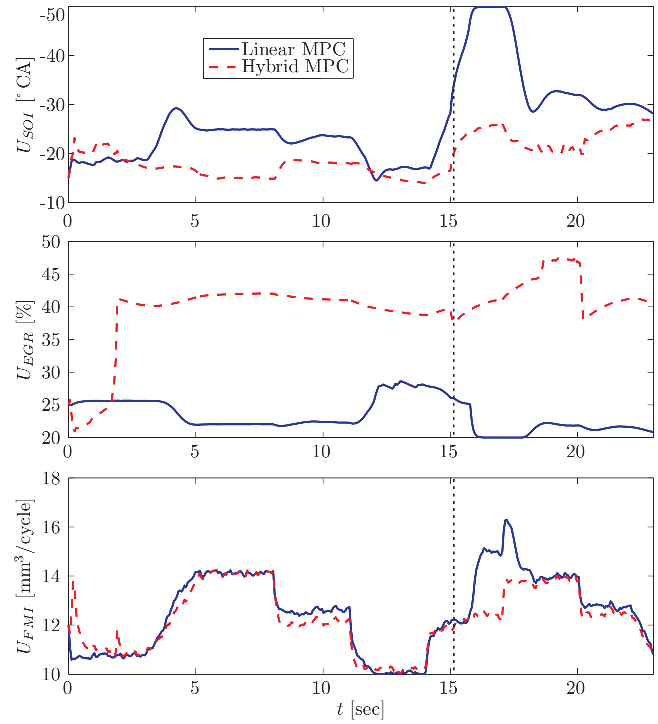

Fig. 4. Closed Loop Result: Actuated variables

VI. CONCLUSIONS AND FUTURE WORKS

In this paper we have presented a complete hybrid control approach for the control of low temperature combustion engines. We have proposed to use correlation clustering algorithms to identify PWA models. By the use of correlation clustering it was possible to identify a PWA model for the complex, nonlinear behavior of the examined PCCI engine. Based on this model we were able to use a hybrid MPC for controlling the engine in different operating modes. We have compared simulation results of the hybrid MPC controller to a linear constrained MPC. It could be shown that the hybrid MPC was much better suited for the control. It is a systematical, model-based approach, which is able to take the nonlinearities of the process into account.

After the successful demonstration, that the hybrid control approach can handle the characteristics of the PCCI engine, the next step will be to reduce the online computation time. Approaches to reduce the computation time are the use of explicit controllers or to parallize the enumerated QP problems. With this computation time reduced controllers, realtime closed loop tests on the testbench will be conducted.

REFERENCES

[1] M. Yao, Z. Zheng and H. Liu: Progress and recent trends in homogenous charge compression ignition (HCCI) engines. In Progress in Energy and Combustion Science, Vol. 35, pp. 398 - 437, 2009.
[2] O. Lang, W. Salber, J. Hahn, S. Pischinger, K. Hortmann and C. Buecker: Thermodynamical and Mechanical Approach Towards a Variable Valve Train for the Controlled Auto Ignition Combustion Process. In SAE Paper 2005-01-0762, 2005.
[3] M. Hillion, J. Chauvin, N. Petit: Combustion Control of an HCCI Diesel Engine with Cool Flame Phenomenon. In Proceedings of the European Control Conference 2009, pp. 3827 - 3832, 2009.
[4] N. Giorgetti, G. Ripaccioli, A. Bemporad, I. Kolmanovsky and D. Hrovat: Hybrid Model Predictive Control of Direct Injection Stratified Charge Engines. In IEEE/ASME Transactions on Mechatronics, Vol. 11, No. 5, pp. 499 - 506, 2006.
[5] P. Drews, T. Albin, K. Hoffmann, A. Vanegas, C. Felsch, N. Peters, D. Abel: Model-Based Optimal Control for PCCI Combustion Engines. In Proceedings of the IFAC-Symposium Advances in Automotive Control, MC 3.2, 2010.
[6] G. Ferrari-Trecate, M. M. D. Liberati, M. Muselli, D. Liberati, and M. Morari: A clustering technique for the identification of piecewise affine systems. In Automatica 39, pp. 205-217, 2003.
[7] H. Nakada, K. Takaba, and T. Katayama: Identification of piecewise affne systems based on statistical clustering technique. In Automatica 41, pp. 905-913, 2005.
[8] E. Achtert, C. Böhm, J. David, P. Kröger and Arthur Zimek: Robust, Complete, and Efficient Correlation Clustering. In Proceedings of the Seventh SIAM International Conference on Data Mining, 2008.
[9] C. Aggarwal and P. S. Yu: Finding generalized projected clusters in high dimensional spaces. In Proceedings of the 2000 ACM SIGMOD international conference on Management of data, pp. 70-81, 2000.
[10] C. Boehm, K. Kailing, P. Kroeger, and A. Zimek: Computing clusters of correlation connected objects. In Proceedings of the 2004 ACM SIGMOD international conference on Management of data, pp. 455-466, 2004.
[11] C. Felsch, K. Hoffmann, A. Vanegas, P. Drews, H. Barths, D. Abel, and N. Peters: Combustion model reduction for diesel engine control design. In International Journal of Engine Reasearch, pp. 359 - 387, 2009.
[12] J. Maciejowsk: Predictive Control with Constraints, Prentice Hall, 2002.
[13] A. Bemporad. Model Predicitve Control Design: New Trends and Tools. In Proceedings of the 45th IEEE Conference on Decision and Control, pp. 6678 - 6683, 2006.
[14] W.P.M.H. Heemels, B. De Schutter, A. Bemporad: Equivalence of hybrid dynamical models. In Automatica 37, pp. 1085 - 1091, 2001.
[15] A. Bemporad, F. Borrelli, M. Morari: Piecewise Linear Optimal Controllers for Hybrid Systems. In Proceedings of the American Control Conference, pp. 1190 - 1194, 2000.
[16] F. Borelli: Predictive Control for linear and hybrid systems. http://www.mpc.berkeley.edu/mpc-course-material, rev. on 03/2011.