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Air-Path Model Predictive Control of a Heavy-Duty Diesel Engine with Variable Valve Actuation ⋆

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Abstract:
In this paper, a model-based strategy for the air-path, fuel injection timing, and fuel pressure control of a heavy-duty Diesel engine is presented. The engine system is a six-cylinder Diesel engine, equipped with a dual-stage fixed geometry turbo system and a variable valve actuation (VVA) system. The VVA operates on the intake valves, and realizes a late Miller combustion cycle. The control strategy implemented is a multilinear - model predictive control (MPC), which manipulates the intake valve hold and closure timing, the fuel injection timing, and the needle opening pressure. The MPC objectives are: (i) to keep NOx emissions under a reference level, (ii) to keep the air-fuel ratio over a certain reference, while (iii) minimizing fuel consumption under other constraints. The use of a model predictive control strategy is motivated by the fact that the system is a multi-input multi-output system, with several constraints applied to it. This paper presents the applied control strategy and simulation results illustrating the potential of the proposed control. The simulation results show that the control strategy is applicable, and that the fuel consumption is minimized, but also that further refinements are required.

Keywords: Diesel engines; Engine control; Model predictive control; Variable valve timing control; Constraints.

1. INTRODUCTION

Environmental requirements of Diesel engines have continuously increased over the last years. Consequently, new developments have been required in order to fulfill the new emissions legislation limits, as well as to improve the performance of the engines, and for example, reducing fuel consumption. Some of those developments have been related to the engines intake valves.

Intake valve closing has a significant impact on the fresh air amount, and thus influences fuel efficiency and engine performance Deng and Stobart [2009]. Alvarenga et al. [2012] proposes a map of the valve management strategies according to the engine operating conditions for an engine with early intake valve closing. Simulation studies have shown the benefits by late intake valve closing (LIVC), brake-specific fuel consumption (BSFC) benefits are shown in Deng and Stobart [2009], as well as the emissions benefits in He et al. [2009]. Different approaches to control intake valve actuation have been demonstrated (Plianos and Stobart [2007], Wu and Wang [2009]). In Plianos and Stobart [2007], a feedback linearization technique is used to control the air system of an engine equipped with intake variable valve actuation (VVA), exhaust gas recirculation (EGR), and variable geometry turbine (VGT). In Wu and Wang [2009], an intake valve actuation governed by a genetic algorithm that minimizes BSFC is proposed.

⋆ This work has mainly been carried out within the EU 7th Framework Program in the EU project CORE.

The additional hardware has increased the complexity of the control strategies with multiple coupled actuators. In order to obtain a desirable behavior of systems with several output variables, by simultaneously manipulating several input variables, a multivariable control is needed. Since the controller not only has to compute the optimal control, but must also deal with a constrained system, the method chosen in this work is the model predictive control (MPC). MPC is a control strategy that uses a model of the system in order to predict future outputs, and to determine an optimal control sequence that optimizes a cost function Camacho et al. [2004], Maciejowski [2002]. The optimal control sequence is computed at each decision instant, and only the first control signal is applied to the system. MPC has already been successfully applied to the Diesel engine air path. In for example, Ferreau et al. [2007], Ortner et al. [2009], Wahlström and Eriksson [2013], MPC was applied to the air-path of Diesel engines equipped with an EGR valve and a VGT.

The main objective of this work is to implement a transient control of a VVA system with LIVC, also called added motion system, using a multivariable controller and model-based techniques.

This paper is organized as follows. In Sections 2 and 3, the problem is formulated. In Section 4, the models used in the proposed control design are described. In Section 5, simulation results are presented and discussed. Finally, Section 6 concludes the paper.

2. PROBLEM FORMULATION

The aim of this work is to design a controller that minimizes the fuel consumption and emissions along a driving cycle. The combustion performance with respect to BSFC, brake-specific oxides of nitrogen (BSNOx), and particulate emissions depends highly on combustion rate and air-fuel ratio (AFR), Lancefield [2003]. The ignition timing depends on advanced fuel injection timing and LIVC timing, Murata et al. [2006]. To avoid particulate emissions a constraint on AFR is applicable. The AFR is related to control of high pressure fuel injection (controlled by needle opening pressure, NOP) and air-charging, Murata et al. [2006]. Consequently, in addition to intake valve timing, also advanced injection timing, and NOP need to be controlled simultaneously. Hence, manipulated variables considered in this context are intake valve hold (IVH), intake valve close (IVC), advanced angle (advanced injection timing) and NOP.

Consequently, the control objectives of the proposed approach, to be translated into an optimization problem in the following section, are:

- Fuel consumption should be minimized.
- NOx emissions should be below a set point NOx^s_{max} (soft limit).
- Air-fuel ratio should be greater than a set point AFR^s_{min} (soft limit).

3. MPC DESIGN

MPC is based on an online optimization and a prediction model of the system, to obtain optimal control actions. A typical MPC scheme involves a linear process model, linear constraints, and a quadratic objective function. It is a quadratic programming (QP) problem which can be solved online with a QP solver efficiently.

The discrete-time state-space linear model used in the MPC has the following form:

$$\begin{aligned} x(k+1) &= Ax(k) + B_c u_c(k) + B_d u_d(k) \\ y(k) &= Cx(k) + D_c u_c(k) + D_d u_d(k) \end{aligned} \tag{1}$$

where A, B_c, B_d, C, D_c, and D_d are the state space matrices, x is the vector of state variables, u_c the control inputs, u_d the measured disturbances, and y the outputs:

$$u_c = [u_{ivh}, u_{ivc}, u_{advangle}, u_{nop}]^T \tag{2}$$

$$u_d = [n_e, u_\delta]^T \tag{3}$$

$$y = [BSNOx, BSFC, AFR]^T \tag{4}$$

This is, the control inputs are IVH (u_{ivh}), IVC (u_{ivc}), fuel injection timing—advanced angle ($u_{advangle}$), and NOP (u_{nop}). The measured disturbances are engine speed (n_e) and injected fuel (u_δ). The model outputs are BSNOx, BSFC, and AFR. Note that the control signals not only include the intake valve timings, but also the advanced injection timing and NOP, which also influences emissions and fuel consumption as was mentioned in Section 2.

The control problem of a Diesel engine air path, to be solved at each sample time, is formulated as an optimal problem with constraints as:

$$\begin{aligned} \min_U \; & q_1 \sum_{j=N_1}^{N_2-1} y_2(k+j+1) \\ & + \sum_{j=0}^{N_c-1} ||u_c(k+j) - u_c(k+j-1)||^2_{Q_2} \\ & + q_3 \sum_{j=N_1}^{N_1+N_c-1} \epsilon_1(k+j+1) \\ & + q_4 \sum_{j=N_1}^{N_1+N_c-1} \epsilon_2(k+j+1) \end{aligned} \tag{5}$$

$$\begin{aligned} \text{s.t.}\; x(k+j+1) &= Ax(k+j) + B_c u_c(k+j) + B_d u_d(k+j) \\ & \quad j = 0, \ldots, N_2-1 \\ y(k+j) &= Cx(k+j) + D_c u_c(k+j) + D_d u_d(k+j) \\ & \quad j = 0, \ldots, N_2 \\ u_c(k+j) &\geq u_{cmin} \qquad j = 0, \ldots, N_c-1 \\ u_{c,2}(k+j) &\geq u_{c,1}(k+j) \quad j = 0, \ldots, N_c-1 \\ u_c(k+j) &\leq u_{cmax} \qquad j = 0, \ldots, N_c-1 \\ u_c(k+j) &= u_c(k+N_c-1) \qquad j = N_c, \ldots, N_2 \\ AFR^s_{min}(k) &\leq y_3(k+j+1) + \epsilon_2(k+j+1) \\ & \quad j = N_1, \ldots, N_2-1 \\ \epsilon_2(k+j+1) &\geq 0 \qquad j = N_1, \ldots, N_1+N_c-1 \\ \epsilon_2(k+j+1) &= \epsilon_2(k+N_1+N_c) \\ & \quad j = N_1+N_c, \ldots, N_2-1 \\ y_1(k+j+1) &\leq NOx^s_{max}(k) + \epsilon_1(k+j+1) \\ & \quad j = N_1, \ldots, N_2-1 \\ \epsilon_1(k+j+1) &\geq 0 \qquad j = N_1, \ldots, N_1+N_c-1 \\ \epsilon_1(k+j+1) &= \epsilon_1(k+N_1+N_c) \\ & \quad j = N_1+N_c, \ldots, N_2-1 \end{aligned} \tag{6}$$

Where ϵ_1 and ϵ_2 are the slack variables representing the constraint violations of the soft constraints, i.e. $\epsilon = 0$ if the constraints are satisfied. N_c is the control horizon, and N_1 and N_2 are the lower and higher prediction horizons, respectively. The first summation of the objective function (5) minimizes the fuel consumption, and the second one penalizes changes in the control signals. The last two summations try to keep the slack variables at zero, if possible.

In (6), hard constraints are imposed on the control inputs, which should belong to the interval $[u_{cmin}, u_{cmax}]$.

The MPC optimization problem is reformulated in the form of a standard QP problem, so that it can be solved using an online QP solver:

$$\begin{aligned} \min_U \; & \frac{1}{2} U^T H U + U^T g(w) \\ \text{s.t.}\; & GU \leq b(w) \end{aligned} \tag{7}$$

with two fixed matrices, the Hessian matrix H and the constraint matrix G; and two vectors depending affinely on a varying parameter w, the gradient vector $g(w) = h+Fw$ and the constraint vector $b(w) = e + Ew$, where

$$w = [x^T(k)\; u_d^T(k) \ldots u_d^T(k+N_2)\; AFR^s_{min}(k)$$
$$NOx^s_{max}(k)\; u_c^T(k-1)]^T \quad (8)$$

H, h, F, G, e, and E are calculated offline from (5) and (6). Note that for solving the optimization problem, a prediction of the disturbances u_d during the prediction horizon N_2 is needed. In this work, it is assumed that u_d is constant within the prediction horizon, and equal to the values measured at time k.

4. LINEAR MODELS

In the operating range of the engine, due to nonlinearities in the system, it is not possible to obtain only one linear model accurate enough for control purposes. The solution chosen in this work is to consider a multilinear approach, i.e. the operating range is partitioned into separate regions and local linear models are applied to each region.

Multiple local linear models are obtained from a highly complex nonlinear gas exchange model of the engine at different stationary operating points. In this way, the MPC uses at each time step, the linear model corresponding to the closest operating point. The operating points are the combinations of positions of the control inputs and values of the measured disturbances, namely IVH positions, IVC positions, advanced angles, nozzle-opening pressures, fuel injections, and engine speeds.

Local linear models suitable for control purposes, and derived uniquely from first principles, could be difficult to obtain and identify. Because of that, in order to capture the dynamics of the engine, the model identification is empirically performed, by completing matrices A, B_c, B_d, C, D_c, and D_d of model (1), given a set of input and output variables

$$y = [y_1, y_2, y_3]^T = [BSNOx, BSFC, AFR]^T. \quad (9)$$

The parameters of the models are estimated using a subspace iteration method described in Ljung [1999]. Low-order models obtained have demonstrated to capture the most important characteristics of the system dynamics. As example of this, Figure 1 depicts the applied input signals, and Figure 2 shows the simulated response of one of the linear models of 4th order and the outputs using the nonlinear model. For this linear model, the normalized root mean square error (NRMSE) that measures the goodness of fit for each output, is approximately 84%, where 100% represents a perfect fit. In average, the NRMSE for all the obtained linear models is 84.5%, showing that the obtained models can capture the dynamics of the system sufficiently.

4.1 State variables estimation

In order to solve the MPC problem stated in (5) and (6), information about the state variables is required. A set of linear observers are used at each time step to estimate the state variables of all the linear models, and in this work, these observers are linear Kalman filters. A brief overview of them is given below.

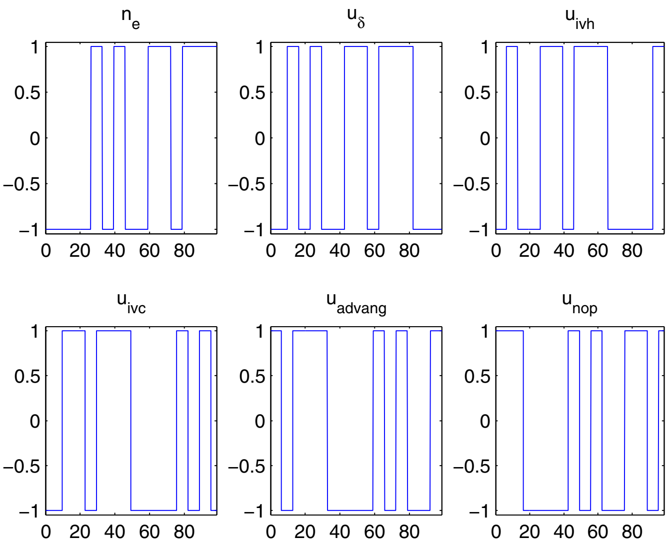

Fig. 1. Input excitation signals used for the identification of the linear models.

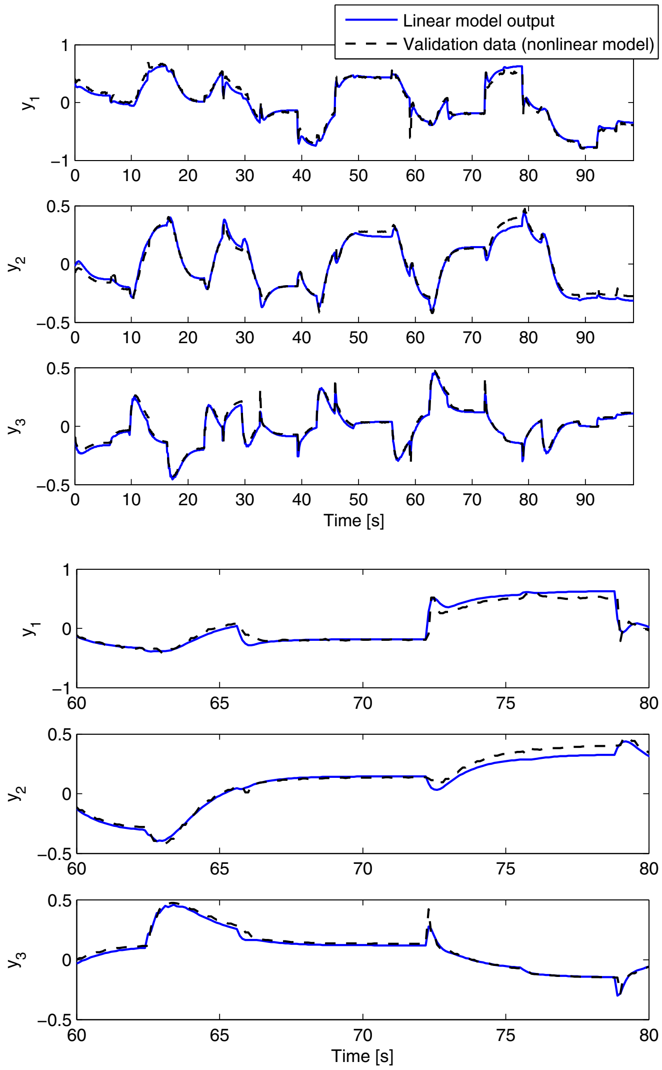

Fig. 2. Comparison of the simulated response of one of the linear models and the corresponding estimates by using the nonlinear model.

The Kalman filter is a well-known method for estimating the state variables of dynamic systems by means of a set of recursive equations, Welch and Bishop [1995]. There are two main steps, the first one "Time Update", and the second one "Measurement Update". In the time update, the states at the current time step are estimated based on the states and its covariance from the previous time step. In the measurement update, the measurement information at the current time step is considered to refine the estimated states. Let us assume that the controlled-process has a state vector $x \in \mathbb{R}^n$, and the process is governed by the linear stochastic difference equation

$$x_k = Ax_{k-1} + Bu_k + w_{k-1}, \tag{10}$$

with a measurement $z \in \mathbb{R}^m$ that is

$$z_k = Hx_k + v_k. \tag{11}$$

The random variables w_k and v_k represent the process and measurement noise, respectively. They are assumed to be independent from each other, white, and with normal probability distributions, process noise covariance Q and measurement noise covariance R.

5. SIMULATION RESULTS

The engine that was used in these experiments, is a six cylinder heavy-duty Volvo Diesel engine with 13 L displacement rated at 460 HP. This six cylinder Diesel engine has a geometric compression ratio of 18:1. A schematic of the engine architecture is presented in Figure 3.

A detailed nonlinear model is used to evaluate the performance of the MPC controller that uses multiple linear

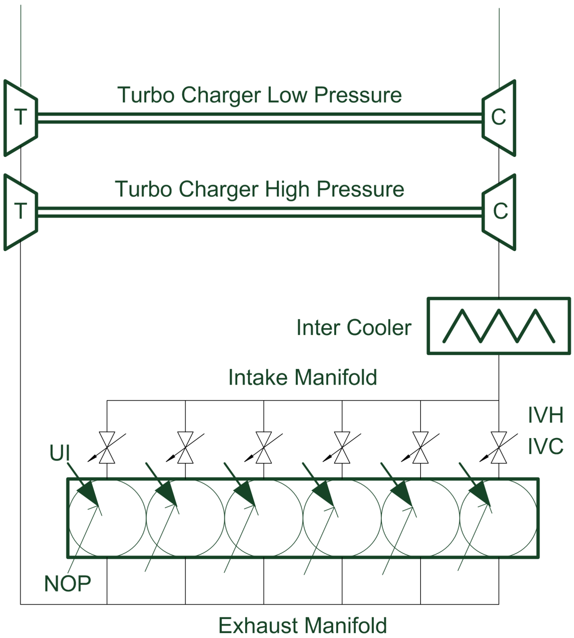

Fig. 3. Schematic drawing of the Diesel engine with VVA used for control and simulation. This figure shows the engine system excluding the after-treatment systems. The engine system comprises: the six-cylinder engine with unit injectors (UI) and NOP for fuel control, the intake valves with IVH and IVC actuation, the dual-stage fixed geometry turbo and charge air cooler (CAC).

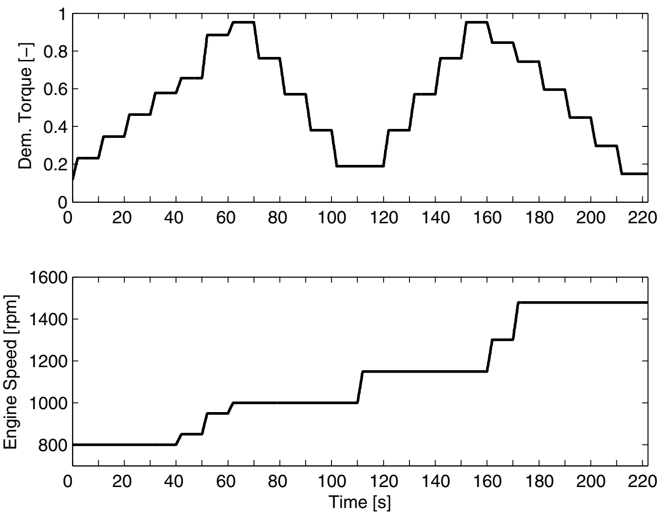

Fig. 4. Illustration of the engine operating cycle used in this study. The upper plot shows the normalized engine torque demand, and the lower plot shows the engine speed.

models. The QP problem of the MPC, (7), is solved using the open-source software package qpOASES, Ferreau et al. [2008].

The number of stationary operating points used to obtain the local linear models is 162. These operating points covers the operating region and are obtained from a regular grid of a 6-dimensional Euclidean space as follows: 3 engine speeds, 3 fuel injections, 2 advance angles, 3 needle opening pressures, and 3 IVH-IVC positions.

The sampling time is set to 100 ms. The control horizon N_c, the lower prediction horizon N_1, and the higher prediction horizon N_2, are set to 2, 10, and 20 samples, respectively.

The input signals, engine speed, and demanded torque, follow a step sequence which changes every 10 seconds as shown in Figure 4.

For a sake of simplicity, the AFR^s_{min} value is assumed constant, so its normalized value λ^s_{min} is:

$$\lambda^s_{min} = \frac{AFR^s_{min}}{AFR_{stoich}} = 1.2$$

The constraint on the engine-out BSNOx, has a maximum value NOx^s_{max}, which changes with time depending on engine speed and torque. The results of two simulation cases are presented in the next.

In the first experiment, the value of NOx^s_{max} is set to a high value in order to show the performance close to an unconstrained NOx situation, see Figure 5. A close look at the figure reveals some oscillations in the control signals. This is due to the modeling errors and their associated discontinuities when switching between different operating points. Although, transient spikes are not observed in the outputs during simulations, in order to decrease the oscillations in the actuators various solutions have been proposed in the literature. In Wahlström and Eriksson [2013], a linear interpolation is done at each sampling instant between the results of two QP problems with

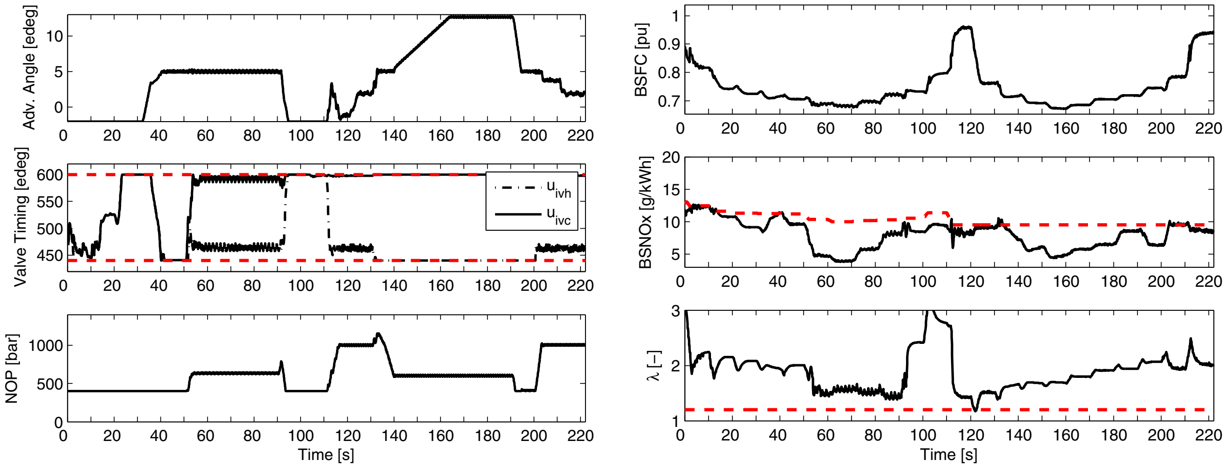

Fig. 5. Control and output signals when constraint on the engine-out BSNOx is set to a high value.

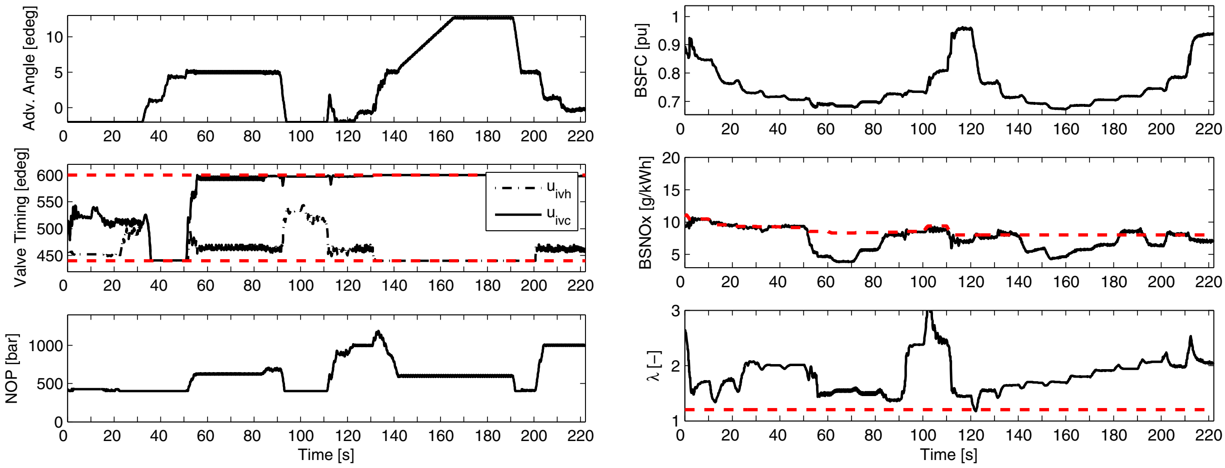

Fig. 6. The constraint on BSNOx emissions is stepped down approx. 2g/kWh for the same controller.

different operating points. In Ortner et al. [2009], a linear parameter varying model is used instead of the multilinear approach, which avoid the switching in the controller.

In the second experiment, the NOx constraint is lowered. Figure 6 shows the ability of the controller to accommodate constraint variations. It is observed that at low engine speed and torque, the VVA system is used to fulfill the NOx requirements. There is a trade-off between NOx and fuel consumption that is defined by using the VVA system in different ways. Compared to the previous case, engine-out NOx emissions have decreased 4.6% along the simulation time, whereas fuel consumption has increased 0.4%.

Figure 7 summarizes the results obtained for the previous two experiments depending on the engine operating conditions. There are three main regions when working at steady state. The first one, where the intake valve closing is delayed the maximum possible. The second one, where the intake valve in not delayed. And the third one, where the intake valve closing (and holding) depends on the NOx emissions soft constraint.

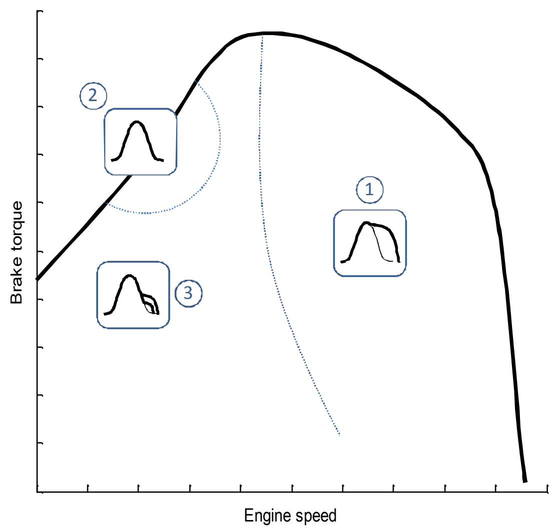

Fig. 7. Map of the LIVC strategies at steady state. Three main regions are distinguished, in particular the third one depends on the NOx emissions limit.

6. CONCLUSIONS

In this work we have developed a multi-input multi-output (MIMO) air path, advanced injection timing, and fuel pressure control of a Diesel engine. We use an MPC approach which combines multiple linear models and a QP optimization algorithm, to give the control actions for each time step.

The simulations have shown good performance in terms of fuel consumption, as well as emissions restrictions, by controlling adequately the VVA actuation.

Future work could be to improve the physical-based non-linear model for transient NOx emission. Other camshaft profile could be needed due to the VVA system is saturated in some points of operation. Another extension could include more extensive case studies, for example transient driving cycles, to test the controller performance. Furthermore, the reduction of the oscillations in the control signals could be subject of future research. Finally, we are planning to test the proposed controller on a test bench.

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