Multiple-Input Multiple-Output Model
Predictive Control of a Diesel Engine

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Abstract: Traditionally, diesel engine control has had to rely on indirect feedback variables and empirical open-loop maps because direct measurements of the variables representing high-level objectives, such as emissions, have not been available in production engines. With new sensors being developed, the opportunity opens to design the controller directly based on high-level objectives. In this paper, we propose to use model predictive control as a systematic way to go directly from high-level specifications to a control algorithm. The controller uses four actuator variables and five measured variables and is based on a model obtained through system identification. Experimental results on a six-cylinder heavy-duty engine around a fixed operating point demonstrate the potential of the control scheme.

1. INTRODUCTION

The high-level objectives of the control system of a heavy-duty diesel engine is to provide a fast response to torque requests from the driver, to ensure a safe operation of the engine, to obtain a low fuel consumption, and to comply with emissions legislation possibly in cooperation with aftertreatment systems. Usually, the variables corresponding to high-level objectives of the controller such as brake efficiency and emissions are not directly available for measurement. Secondary variables are instead used for feedback and feedforward control, such as pressures and temperatures at various locations in the engine (Guzzella and Onder (2004)). Empirical maps (often based on steady-state data) are then used to find optimal settings for the actuators and secondary variables in terms of the high-level objectives.

To satisfy the high-level goals, a set of actuator variables are available. The most widely used in published studies on diesel engine control are exhaust gas recirculation (EGR) and variable geometry turbo (VGT) valve positions (Omran et al. (2009); Örtner and Re (2007)), fuel injection parameters (Hafner et al. (2000)), variable valve actuation (Yilmaz and Stefanopoulou (2003)), or some combination of these (Karlsson et al. (2008); Hillion et al. (2008)). Modern diesel engines in production are equipped with at least actuation of EGR, VGT, and fuel injection.

In practice, there are interactions between all actuator variables and both measured variables and high-level objectives. Therefore, control design is a highly complex task. To make the problem manageable, the design of airpath and fuelpath controllers are traditionally treated as two separate tasks, considering only static interactions between the two systems. In recent years, much focus has been put on low temperature diesel combustion (LTC) achieved through high levels of exhaust gas recirculation (EGR) and suitably chosen fuel injection timings (Musculus (2006)) as a means to reduce emissions of NOx and soot particles from the engine. LTC combustion is more challenging from a control perspective than traditional diesel combustion because of tight requirements on emissions. Also, the time constants in the engine dynamics are generally longer because EGR flow and heating and cooling of e.g. cylinder walls play a greater role in the resulting combustion process. This development accentuates the need to consider interactions between fuel injection and airpath controllers, as noted in e.g. (Hillion et al. (2008); Alberer (2009)).

The goal in diesel engine control design is to optimize engine operation. Much research effort has been spent on good models and control design solutions for low-level control loops considering e.g. only the airpath control. With today’s sophisticated engines, the over-all control design task involves many actuators, measurements, subsystems, interactions, experimental maps, models, conflicting optimization criteria, and constraints. In this paper, we propose to start the control design task from a high-level perspective. The high-level control task of optimizing a trade-off of several variables subject to a large number of constraints fits nicely into the formulation of model predictive control (MPC). In the work, the most important actuator variables were considered simultaneously, namely EGR valve position, VGT vane position, start of fuel injection, and fuel injection duration. As far as possible, measurements directly related to high-level objectives were used for feedback, i.e., direct measurement of NOx, opacity measurement for soot, and measurements of indicated mean effective pressure (IMEP), combustion phasing, and peak pressure derivative from in-cylinder pressure sensors.

The purpose of the paper is to demonstrate the potential of approaching the control design task from a top-down perspective starting with high-level control using multiple-
input multiple-output MPC and direct measurements of emissions. There are many opportunities for future improvements of the scheme through putting more attention into low-level details, such as adding low-level control loops from e.g. EGR valve position to mass flow.

The paper is organized as follows. In Section 2, the experimental equipment is presented and details are given on actuator variables and measured variables. Section 3 discusses design of the model predictive controller. Section 4 presents experimental results, and advantages and remaining issues for the control scheme are discussed in Section 5. Finally, conclusions are made in Section 6 and directions for future work are pointed out.

2. EXPERIMENTAL EQUIPMENT

The experiments were conducted on a six-cylinder turbocharged heavy-duty diesel engine. Engine specifications are given in Table 1. The engine was equipped with unit injectors for diesel where fuel injection timings could be set individually for each cylinder, with a low-pressure exhaust gas recirculation (EGR) loop where the EGR rate could be adjusted by a valve in the exhaust pipe, and with a variable geometry turbo (VGT) where the turbocharging also could be adjusted. The setup allows for four manipulated variables

\[ u = (u_{SOI} \quad u_{FD} \quad u_{EGR} \quad u_{VGT})^T \]

where \( u_{SOI} \) is the crank angle degree of start of injection, \( u_{FD} \) the fuel injection duration measured in crank angle degrees, \( u_{EGR} \) the position of the EGR valve, and \( u_{VGT} \) the position of the VGT vanes. The fuel injection variables were updated each engine cycle, and the valve position variables were updated with a frequency of 10 Hz.

All cylinders were equipped with piezo-electrical, water-cooled pressure transducers of type Kistler 7061B, with cylinder pressure data sampled every 0.2 crank angle degrees using a Microstar DAP 5400a/627 data acquisition board. The pressure measurements \( p \) from the in-cylinder pressure sensors were used to compute indicated mean effective pressure, \( y_{IMEP} \), combustion phasing \( \alpha_{50} \), and maximum pressure derivative \( d_p \). The indicated mean effective pressure is defined as

\[ y_{IMEP} = \frac{1}{V_D} \int pdV \]

where the integral is taken over an engine cycle, and the maximum pressure derivative as

\[ d_p = \max_{\theta} \frac{dp}{d\theta} \]

From the cylinder pressure \( p \), the heat release rate \( dQ \) is computed using the relation

\[ \frac{dQ}{d\theta} = \frac{\gamma}{\gamma - 1} p(\theta) \frac{dV}{d\theta} + \frac{1}{\gamma - 1} V(\theta) \frac{dp}{d\theta} \]

for the apparent heat release rate based on a fixed ratio of specific heats (Heywood (1988)). From the heat release rate, \( \alpha_{50} \) is defined as the crank angle degree where 50 % of the heat has been released.

Emissions of \( NO_x \), \( y_{NO_x} \) were measured using a Siemens VDO / NGK Smart NOx Sensor. Soot emissions, \( y_{op} \) were measured using an opacimeter from SwRI measuring the percentage of light absorbed by the exhausts in the exhaust pipe. Formation of soot is highly nonlinear, with gain from actuator variables to measured opacity being much higher at high soot levels compared to lower levels. In order to make the process more linear to facilitate closed-loop control, opacity was rescaled based on an inverted empirical map when used for system identification and feedback to the controller.

Five measured variables were thus used in the control design,

\[ y = (y_{IMEP} \quad \alpha_{50} \quad d_p \quad y_{NO_x} \quad y_{op})^T \]

The control system was based on a standard PC running Linux enabling cycle-to-cycle control. Controllers were designed in Simulink and converted to C-code using Real-Time Workshop.

3. CONTROL DESIGN

3.1 High-level Specifications

Several high-level objectives should be fulfilled in the control design:

- Fast reference tracking of torque.
- Low specific fuel consumption.
- Low average emissions of \( NO_x \).
- Low average emissions of soot.
- Limited emission peaks during transients.
- Limited peak pressure derivatives to avoid audible noise and damage to the engine.

These high-level objectives need to be mapped into specifications on the available control variables and measured variables of the engine.

3.2 Modelling

The controller was based on a dynamic state-space model of the engine obtained through system identification (Johansson (1993)). In (Karlsson et al. (2010)), it was shown that identified linear models could predict outputs well at fixed operating points, and further that linear models at different operating points could be combined into Wiener models which promises to provide good prediction over a large operating range using a limited set of dynamical models. In the present work, control around a fixed operating point is studied. A fixed sixth-order linear model of the form

\[ x_{k+1} = Ax_k + Bu_k + Kw_k \]
\[ y_k = Cx_k + Du_k + w_k \]

where \( u_k \in \mathbb{R}^4 \), and \( y_k \in \mathbb{R}^5 \) was used for control design.

The model step response is shown in Figure 1. The model incorporates both fast dynamics, as in e.g. the step response from \( u_{SOI} \) to \( \alpha_{50} \) which is almost instantaneous,
and slow dynamics as e.g. the step response from $u_{EGR}$ to $y_{NOx}$ which takes more than 100 cycles to settle.

### 3.3 Model Predictive Control

The Model Predictive Control Toolbox of Matlab R2008b was used to design the controller.

The formulation is based on optimization of the cost function

$$J(k) = \sum_{i=1}^{H_p} \mathcal{J}(i|k) + \sum_{i=1}^{H_p} \mathcal{U}(i|k) + \rho_k \varepsilon^2 \quad (7)$$

where

$$\mathcal{J}(i|k) = \sum_{j=1}^{N_p} w_j^y (r_j y(k) - \hat{y}_j(k + i|k))^2$$

$$\mathcal{U}(i|k) = \sum_{j=1}^{N_p} w_j^u (r_j^u - \hat{u}_j(k + i|k))^2 + \sum_{j=1}^{N_p} w_j^{\Delta u} \Delta \hat{u}_j(k + i|k)^2$$

subject to the constraints

$$y_{\min} - \varepsilon V_{\min}^y \leq y(k) \leq y_{\max} + \varepsilon V_{\max}^y$$

$$u_{\min} - \varepsilon V_{\min}^u \leq u(k) \leq u_{\max} + \varepsilon V_{\max}^u$$

$$\Delta u_{\min} - \varepsilon V_{\min}^{\Delta u} \leq \Delta u(k) \leq \Delta u_{\max} + \varepsilon V_{\max}^{\Delta u}$$

$$0 \leq \varepsilon$$

for the system

$$x_{k+1} = Ax_k + Bu_k + Kw_k$$

$$y_k = Cx_k + Du_k + w_k$$

The optimization is computed over the control moves $\Delta u(k + i|k)$ at a set $T_u$ of specified control action times $i \in T_u$, and over the slack variable $\varepsilon$ (Maciejowski (2002)). A Kalman filter is used for output prediction based on a noise model obtained through system identification.

Automatic code generation using Real-Time Workshop from a Simulink model of the controller was used to translate the controller into C-code which was later compiled into an executable program that could be used for real-time control.

The following design choices were made in the setup of the model predictive controller:

- A high weight was put on reference tracking of $y_{MEP}$ to get a fast torque response.
- A reference value was set for $\alpha_{SOI}$ to achieve combustion phasing close to maximum brake torque timing. Prior information is needed to determine the correct reference value.
- A reference value of 0 was specified for $y_{NOx}$.
- A load-dependent reference value was set for $y_{op}$. The reference value was set low enough to avoid excessive soot formation. The exact value should be determined considering the aftertreatment system used.
- A maximum limit was set on $y_{op}$ to avoid very large peaks in soot emissions during transient operation where reference tracking of $y_{MEP}$ would otherwise take precedence over keeping the reference value for $y_{op}$. Such high values of soot emissions may exceed the capacity of the aftertreatment system for soot, and may also clog engine pipes.
- A maximum limit was set on $d_p$ to avoid excessive audible noise.
- A target value was set for $u_{VGT}$. Without such a target, maximum allowed turbocharging would be applied in stationarity in order to obtain the best possible NO$_x$-soot trade-off. In such case, $u_{VGT}$ would lose control authority through saturation during transients, and fuel consumption might also suffer.
- A slack variable was used for constraint softening.
- Constraints were specified for minimum and maximum values and rates of all control variables in order
Experimental results for changes of reference value for $y_{\text{IMEP}}$ around the chosen operating point are shown in Figure 2. It can be seen that reference tracking of $y_{\text{IMEP}}$ is fast and accurate. A change of load from $y_{\text{IMEP}} = 6$ bar to $y_{\text{IMEP}} = 8$ bar is achieved in 7 engine cycles corresponding to 0.7 s at an engine speed of 1200 rpm. The variance in $y_{\text{IMEP}}$ is substantially larger at load $y_{\text{IMEP}} = 6$ bar, indicating that the model is less accurate at this operating point.

When load is increased at engine cycle 250, opacity increases and momentarily exceeds the limit. The controller takes several actions to bring down opacity. When the load reference value is increased, the EGR valve is adjusted to reduce the amount of recycled exhaust gases, and thus reducing soot formation. Injection timing is also advanced in order to get earlier combustion and less soot formation.

4. EXPERIMENTAL RESULTS

4.1 Change of reference load

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Airpath and fuelpath actuators are thus automatically coordinated to satisfy control objectives.

Also, the controller successfully combines feedforward and feedback functionality. When load is increased, the model predicts that opacity will exceed the limit and immediately adjusts $u_{\text{EGR}}$ and $u_{\text{SOI}}$ — corresponding to feedforward control. When the measured opacity exceeds the limit a few cycles after the change in reference load, all variables are further adjusted to quickly bring opacity below the limit — corresponding to feedback control.

Combustion phasing $\alpha_0$ is maintained close to its reference value throughout the experiment. Peak pressure derivative $d_p$ never approaches its limit of $d_p = 20$ bar/CAD during the experiment. Emissions of NO$_x$ are minimized subject to constraints and reference values of all other variables throughout the experiment. Compared to other variables, $y_{\text{NOx}}$ varies slowly throughout the experiment. This is due to the fact that NO$_x$ formation is influenced by many slow processes such as EGR flow and heating and cooling of cylinder walls (see Figure 1), as well as response time in the NO$_x$ sensor (0.75 s for 33% to 66% rise). The influence of the VGT is negligible at the investigated operating point, and it is kept close to its setpoint.

4.2 Change of reference load and speed around the operating point

Figure 3 show experimental results for changes of both load and speed around the reference point. Tracking of $y_{\text{IMEP}}$ is accurate throughout the experiment, tracking of $\alpha_0$ is successful except for the cases where load is
increased and the opacity limit is exceeded. Emissions of NO\textsubscript{x} are as low as possible given the specifications on opacity. The controller appears to be fairly robust to changes in load and speed in the investigated operating range.

4.3 Influence of opacity constraint

Figure 4 shows a load change from \( y_{\text{IMEP}} = 6 \) bar to \( y_{\text{IMEP}} = 8 \) bar for two different experiments. The first, labeled ‘original’ is the same as shown in Figure 2. In the second experiment the same controller was used, except that the constraint on opacity was removed. As can be seen, the peak in opacity after the change of reference load is larger for the second case. The largest difference between the two controllers can be seen in \( u_{\text{SOI}} \) and \( \alpha_{50} \). With the opacity constraint present, the controller advances combustion phasing compared to the setpoint in order to reduce opacity.

5. DISCUSSION

The goal of the work presented here has been to use MPC as a way to go from high-level specifications into a control algorithm in a systematic, intuitive manner. The long-term vision is to use as little a priori information gathered through experimental data as possible, and leave the multi-criterion optimization up to the controller based on sensor information. There would be many advantages in using MPC in such way. The experimental efforts needed for control system development could be reduced when online optimization replaces precalibrated experimental maps. The controller could more easily adapt to engine wear and shifting environments. There is also a great potential in designing the optimization criterion, setpoints, and constraints considering the requirements of the aftertreatment system.

The methodology in this paper has come some way towards the goal, but is not yet complete. The following a priori information is used for the controller:

- A load-varying setpoint for opacity. It would be desired to replace this with a fixed setpoint based on what the aftertreatment system can handle.
- A setpoint for \( \alpha_{50} \) that is determined to be optimal in terms of fuel consumption. It would be better to directly measure fuel consumption and use that for feedback control. However, some effort is required to integrate fuel consumption optimization into the MPC formulation. Fuel consumption cannot be modelled as the output of a linear(-ized) model of type (6) because at the optimum it is not a monotonically increasing/decreasing function of the control variables. Some extremum-seeking feature must be included into the controller to minimize fuel consumption online.
- A setpoint for \( u_{VGT} \), also obtained from experience on optimal settings for fuel consumption. This setpoint should be removed and instead handled through online optimization of fuel consumption.
- Experimental data is required for identification of a dynamic model. It would be desirable to replace it.
Fig. 4. Experimental results for a load increase. The original controller has a constraint on $\gamma_{op}$ which it fulfills by advancing combustion phasing. The controller without opacity constraint keeps the setpoint for $\alpha_{50}$ at the expense of a larger peak in $\gamma_{op}$ during the transient. The engine speed was fixed at $N = 1200$ rpm. by a (semi-)physical model, possibly with physical models for lower level control loops combined with a higher-level model obtained through system identification.

A drawback of the proposed control scheme is that it relies completely on sensors that are not available in production heavy-duty diesel engines today, namely an opacimeter and in-cylinder pressure sensors. Naturally, it would be desirable to remove the need for such sensors and find reliable ways of estimating the quantities from other measured variables. Though interesting progress has been made along this path, see e.g. (Alberer (2009)), we believe it is still of interest to study what can be accomplished if we assume that all desired measurements are available.

6. CONCLUSIONS

Model predictive control was used for control of a heavy-duty diesel engine with the aim of simultaneously controlling load, combustion phasing, and emissions in an optimal way with correct trade-offs both in steady-state and during transients. The controller used direct measurements of emissions which facilitates relating high-level specifications to design of a control algorithm. Experimental results demonstrated the potential of the controller to use the available degrees of freedom from the actuators to achieve several objectives simultaneously.

The work presented here used a single linear dynamical model obtained from system identification in a fixed operating point. In future work, gain-scheduling of several linear models assembled at different operating points could be tested to control the engine in a larger operating range. There is also potential in improving the control scheme by adding more sensors and closing low-level control loops from e.g. valve positions to mass flow. Also, cylinder balancing needs to be considered.

REFERENCES


