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Modeling, Identification and State estimation of Diesel Engine Torque and NOx Dynamics in response to fuel quantity and timing excitations

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ABSTRACT

A systems approach to modeling the response of brake torque and NOx emissions of a high-speed common-rail diesel engine to combined excitations in fuel quantity and timing is investigated. A multivariate mean-value model is proposed, identified and validated. The model structure is derived from and extends an existing physical model [1, 2]. This model structure is linearized and its parameters are then identified at selected engine operating points. Observers are presented for the physically based model and it is shown that Torque and NOx can be predicted using existing measurements of manifold pressure and mass air flow.

1. INTRODUCTION

The common-rail diesel engine is a complex, multivariate system. The modern turbocharged Diesel engine poses intriguing research problems in the area of model-based dynamic system control. **Figure 1** shows a schematic of a turbocharged common-rail direct-injected diesel engine with exhaust gas recirculation (EGR).

For the purpose of analysis, the Diesel engine can be partitioned into two subsystems-

1. The air loop consisting of the turbocharger, intercooler, the EGR valve and EGR throttle (if present), and
2. The fuel system comprising of the fuel pumps, fuel pressure regulator, high pressure accumulator (common-rail) and the fuel injectors.

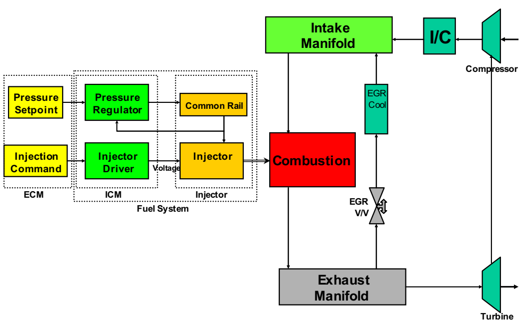

Fig. 1 Schematic of a turbocharged Diesel engine with EGR

The air-loop and the fuel system are coupled through the combustion process. The main control inputs to the system are the commanded fuel quantities and fuel timings, the EGR valve position command and the VGT vane position. The system outputs are engine brake torque, engine speed and pollutant emissions such as CO, CO_2, HC, PM (soot), and NOx., which may be considered to be the undesirable byproducts of the combustion process.

The behaviour of the primary air-loop outputs, *MAP* and *MAF* as a function of EGR and VGT commands follow complex nonlinear dynamics. [1-4] stand out among the several attempts to formulate control-oriented models for this system. A 3-state nonlinear model is proposed in [1] based on simplifying assumptions which is further modified in [2]. In [3-4], the authors present controller development using both nonlinear and linear frequency domain models. The general approach followed in these approaches is to treat the fuel system as a known external disturbance, and develop models parametrized by the fuel injection related influence variables. The engine torque and emissions are related to the inputs via regressions involving the intermediate model state variables. Setpoints for the controllers are obtained via static optimization of the output maps. The popular approach to modeling engine torque is to treat it as a static nonlinear function of air/fuel ratio as adopted in [6-7]. The other approach is to treat it as a first order delay in response to fueling rate, [8].

The survey above indicates that while the air-loop has been studied extensively from a systems perspective, the same is not true for the fuel path. In this paper, we present approaches for modeling the combined *dynamic* influence of fuel quantity and timing on the brake Torque and NOx. The ultimate goal of this study is to come up with multivariate control-oriented models of the Torque/NOx dynamics with respect to fuel quantity and timing as the control inputs. The influence of fuel timing towards the reduction of PM and NOx is well known. Hence, it is only natural to include fuel timing as part of the control input vector. This is essential to maintain an acceptable trade-off between the performance and emissions of a Diesel engine. In order to develop dynamic control methodologies using fuel timing, dynamic models are essential. This is the goal of this paper.

2. PLANT AND EXPERIMENTAL SETUP

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The particular engine used in this study is a 2.5 l, 4 - cylinder VM-DDC direct-injection, turbocharged (fixed-vane), intercooled and wastegated engine with cooled EGR. Table 1 shows the relevant engine parameters.

Configuration	In-line 4
Displacement	2499 cc
Bore and Stroke	92 mm x 94 mm
Compression Ratio	17.5:1
Specific Power	41.2 kW/liter
Min. BSFC	210 g/kW hr.
Rated Power	103 kW @ 4000 RPM
Peak Torque	340 Nm @ 1800 RPM

Table 1. Engine parameters

Brake torque was measured using the dynamometer load-cell and NOx was measured using a Horiba emissions bench. The fueling and EGR commands were implemented using a separate controller, leaving the stock control unit to perform only the rail pressure control function.

3. MODELING AND IDENTIFICATION

MODEL STRUCTURE

There are several ways in which the modeling activity can be approached. The control designer has the choice of designing linear or nonlinear models. Each class of models can be based on either physical principles , pure black-box modeling or a combination of both. In this paper, we propose a linear grey-box approach to modeling the torque and NOx dynamics in response to combined fuel quantity-timing excitation. This model is grey-box in the sense that its structure is physically motivated, but the parameters are determined purely through system identification. The linear aspect is motivated by the observations presented in the introduction. It will be demonstrated that this model structure is quite adequate in predicting the torque and NOx dynamics.

The proposed model structure is represented by the following state-space equation:

$$
\begin{aligned}
&x(k+1) = Ax(k) + Bu(k), \\
&x = [p1 \quad p2 \quad maf \quad \tau \quad nox]^T \in R^5 \\
&u = [pw \quad \delta]^T \in R^2
\end{aligned}
\tag{1}
$$

The states and inputs and their units are defined according to (2), starred quantities denoting nominal values. The delta notation has been dropped for brevity, and lowercase letters are used instead to denote the perturbations. The timescale of the index k is approximately one engine cycle, as will be explained in the next section.

$$
\begin{aligned}
&p1 = P1 - P1^*,\ Bar,\ p2 = P2 - P2^*,\ Bar \\
&maf = MAF - MAF^*,\ g/s \\
&\tau = T - T^*,\ Nm,\ nox = NOx - NOx^*,\ ppm \\
&pw = PW - PW^*,\ \mu\text{sec} \\
&\delta = SOI^* - SOI,\ \deg rees\,CA
\end{aligned}
\tag{2}
$$

p1 is the intake manifold or boost pressure (MAP), *p2* is the exhaust manifold pressure (EXMAP) and *maf* is the compressor air flow-rate. The fuel quantity is represented by the commanded pulse-width, being directly proportional to it either on a per-cycle basis or at a constant speed. The definition of the timing input δ can be interpreted as injection advance. The positive direction indicates increase in NOx (in the range of timings retarded from MBT). The B matrix has a special structure, given by

$$
\begin{bmatrix} 0 & x & 0 & x & x \\ 0 & x & 0 & x & x \end{bmatrix}^T \tag{3}
$$

Hence, the control *directly* influences only the p_2, torque and NOx dynamics. This model in equations (1)-(3) is motivated by the 3-state model proposed in [1] and later modified by [2]. The original intetnt of this model was to solve the air-loop related control problems with fueling rate assumed to be available as a known disturbance input. The original nonlinear model is given by the following equations:

$$
\begin{aligned}
&\dot{p}_1 = \frac{RT_1}{V_1}\left(\frac{\eta_{cis}}{T_a C_p} \frac{P_c}{\left[\left(\frac{p_1}{p_a} \right)^{\gamma-1/\gamma} \right] - 1} - k_e p_1 + W_{egr} \right), \\
&\dot{p}_2 = \frac{RT_2}{V_2}\left(k_e p_1 + W_f^d - W_{egr} - W_{2t} \right) \\
&\dot{P}_c = -\frac{1}{\tau}\left(P_c - \eta_m \eta_{tis} T_2 c_p \left(1 - \left[p_a / p_2 \right]^{\gamma-1/\gamma} \right) W_{2t} \right)
\end{aligned}
\tag{4}
$$

Pc is the compressor power. It is related [5] to the compressor air flow-rate Wc (maf) through

$$
\begin{aligned}
&P_c = \phi_c(p_1) W_c, \\
&\phi_c(p_1) = \left(\frac{T_a c_p}{\eta_c} \right) \left[\left(\frac{p_1}{p_a} \right)^{\mu} - 1 \right],
\end{aligned}
\tag{5}
$$

The EGR and turbine flows, W_{egr} and W_{2t}, are nonlinear functions of the states and the inputs α and β (EGR and VGT valve/vane positions respectively) (Jankovic, 1998).

$$
W_{EGR} = C_1(\alpha) \frac{p_2}{\sqrt{RT_2}} \Psi_1\left(\frac{p_i}{p_j} \right), p_i = \min(p_1, p_2), \tag{6}
$$

$$W_{2t} = C_2(\beta)\frac{p_2}{\sqrt{RT_2}}\Psi_2\left(\frac{p_2}{p_a},\beta\right) \quad (7)$$

In the approach presented here, we constrain α and β to be fixed parameters (note that our plant is wastegated and hence β is inherently fixed). This allows us to insert expressions for the EGR and turbine flows into (4). The structure proposed in (1) can then be derived from (4)-(7) by first changing coordinates from *Pc* to *maf*, linearizing about nominal engine operating conditions and finally discretizing the resulting equations.

MODEL IDENTIFICATION

The parameters identified for the linearized model can be considered to be functions of the nominal state/input and the remaining parameters that were held fixed. These parameters included engine speed, EGR valve command, rail-pressure and pilot injection parameters (timing and quantity).

The model was identified at 1800 RPM with the main pulse start-of-injection (SOI) varying between 0 and -2 degrees ATDC and the main fuel pulse width varying between 500 μsec and 600 μsec. The operating conditions for identification of this model are summarized in Table 2. Figure 2 shows the input scheme that was used in identifying the MIMO dynamic model.

Load point	**Main PW (usec)**	**Main SOI (deg ATDC)**
1	500	0
2	500	-2
3	600	0
4	600	-2
Engine Speed (RPM)	**Pilot PW (usec)**	**Pilot timing (degCA)**
1800	200	-20

Table 2 Operating conditions for model identification

The overall timing perturbation of 2 degrees may be considered to be small. It is well known in literature that the static effect of timing is quite nonlinear, especially around MBT. This was verified in our experimentation and it was found that the DC gain variation in the chosen range was reasonably linear. Moreover, the sensitivity of NOx to timing is much higher than to the fuel quantity, and the chosen range represents a significant percentage of the plant output range. It will also be demonstrated in a later section that the identified model actually performs adequately for larger timing perturbations.

The sampling rate for the test data was 240 Hz, or 16 times per engine cycle at 1800 rpm. The NOx signal was time-advanced by approximately 68 engine cycles to eliminate the transport lag resulting from the long sampling line to the emissions bench.

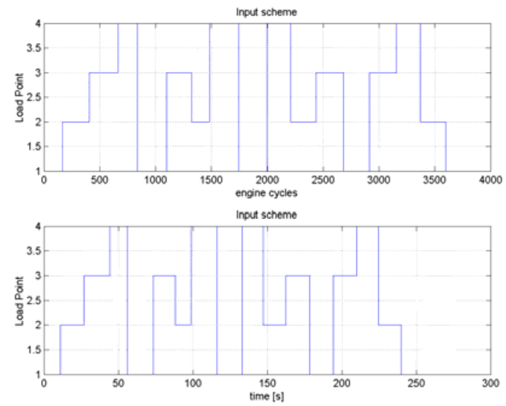

Fig 2 Input scheme for MIMO model identification

Table 3 shows the identified model eigenvalues of the linearized model identified inside the quadrilateral defined by the operating points points noted in Table 2.

	Eigenvalues(A)
	-0.0055 0.4741 0.9289 + 0.0442i 0.9289 - 0.0442i 0.9720
	Table 3 Model eigenvalues

Figure 3 shows the performance of the model for Torque and NOx prediction on the identification data-set. The x-axis is represented in engine cycles. Each time-step of the identification data set is now approximately equal to an engine cycle as a result of decimation. This is therefore truly a mean value model.

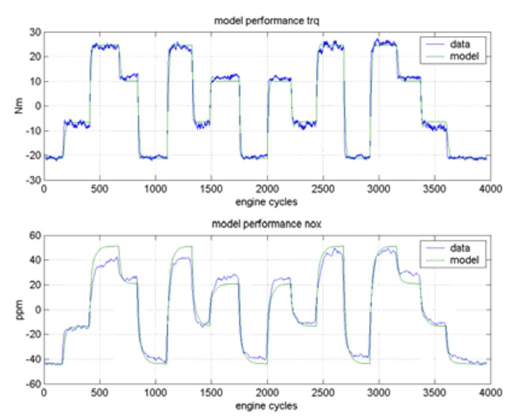

Fig. 3 Torque and NOx prediction on the identification data-set

Rise time and fall time for both Torque and NOx during the steps are approximated satisfactorily by the model. Also, in general, the DC gains are approximated quite well, especially given the fact that the Torque measurement remains quite noisy even after filtering. Predictions for the remaining states are presented in fig. 3.

From Figure 4 we see that *p1* and *maf* predictions are very good. *p2* predictions are also satisfactory except towards the end of the cycle. A closer examination of the data reveals that this is due to drift and gain change in the plant response (e.g., compare the plant response for *p2* at 500 and 3000 engine cycles, both at load point 3).

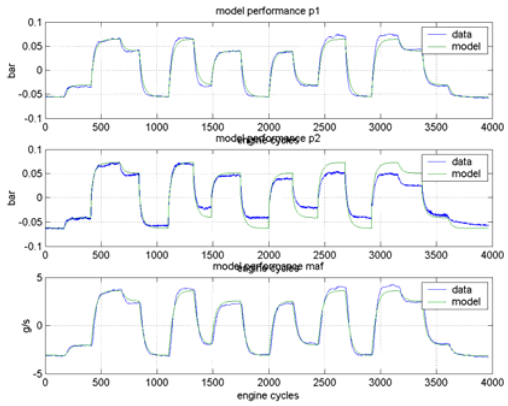

Fig. 4 *p1*, *p2* and *maf* prediction on the identification data-set

Table 5 shows the residual statistics for the model on the identification data set. From this it is evident that p1 and maf are predicted the best. Model fits were computed using the following expression:

$$fit = \left[1 - \frac{\|y - \hat{y}\|}{\|y - \bar{y}\|}\right] * 100 \qquad (8)$$

where y is the particular signal of interest, $\hat{y}$ is the prediction and $\bar{y}$ is the mean of that data sequence. The fit denotes the % of data variance explained by the prediction.

It is evident that the model predictions explain a significant portion of the data. The mean absolute errors are within 3%. The torque production shows a relatively high maximum error. Further analysis indicates that this error does not occur at DC but during transients where the model prediction lags the plant response (e.g., around the 2695 engine cycle mark).

Signal	**Mean abs % error**	**Max abs % error**	**Model Fit**
P1	0.3495	1.7495	87.4463
P2	0.8640	3.7648	70.0978
maf	0.5393	3.3088	87.2892
Torque	1.8991	28.1054	87.0764
NOx	2.2185	13.3605	79.7381

Table 4 Model residual statistics on identification data

Model Validation

The operating conditions for validation of this model are summarized in Table 5. This operating condition is significantly different from the identification data-set in a variety of ways. The fuel quantity range is the same, but the points lie on both the interior and exterior of the identification range. Secondly, the fuel timing range is larger than that used for identification. A range of 4 degrees CA can be considered to be reasonably large, given the sensitivity of the engine to timing. Another difference is in the pilot injection quantity. This gives us an opportunity to explore whether this parameter has a significant influence on our identified model.

Load point	**Main PW (usec)**	**Main SOI (deg ATDC)**
1	450	0
2	450	-4
3	550	0
4	550	-4
Engine Speed (RPM)	**Pilot PW (usec)**	**Pilot timing (degCA)**
1800 RPM	100	-20

Table 5 Operating conditions for model validation

Figure 5 demonstrates that torque and NOx predictions of the model are satisfactory. *p1* and *maf* predictions are also consistent, but *p2* is not well predicted. This is also reflected in the model fits. The high maximum error for torque prediction occurs during a transient part as before.

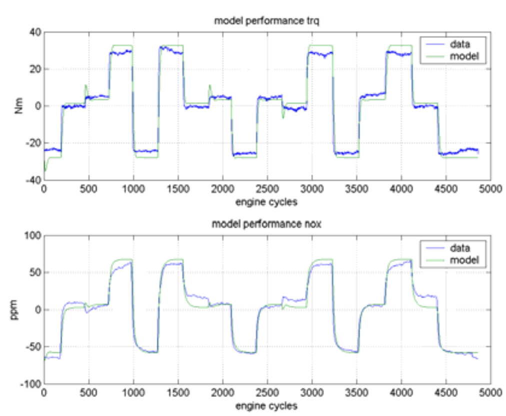

Fig. 5 Torque and NOx prediction on validation data-set

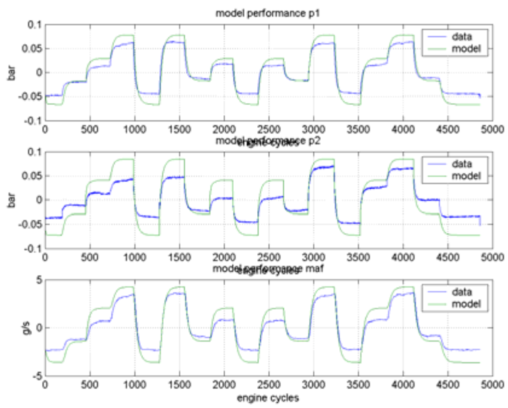

Fig. 6 *p1*, *p2* and *maf* prediction on validation data-set

Signal	Mean abs % error	Max abs(% error)	Model Fit (% variance explained)
P1	1.1261	2.4869	60.9074
P2	2.0383	7.4524	21.5630
maf	2.0922	3.6091	53.4815
Torque	5.6415	57.7947	78.5878
NOx	2.9216	19.3115	81.0828

Table 6 Model residual statistics on validation data

Model Validation 2- Effect of EGR variation

Apart from validating the model on a different operating range, it is also interesting to explore how the identified model (and the plant) behave under parameter variations. The previous sub-section showed that the model and plant behaviour do not change significantly under variation of pilot quantity. In this section we will explore another parameter, namely the EGR valve command, which has the strongest influence on NOx.

Figure 7 shows the DC behaviour of Torque and NOx in response to EGR valve command. This reveals an interesting fact. The DC value of the system response (NOx) varies almost linearly with EGR valve command between 40% and 70% points. The second interesting observation is that the torque and NOx trajectories corresponding to the different load points are almost parallel in this range. This leads us to believe that EGR affects the plant essentially as a bias, without changing the linear system gain. Note that the load points used in this figure correspond to table 5.

Figures 8 and 9 show the Torque and NOx response for the plant under two different EGR conditions- fully shut and fully open. As an indication of EGR rate, the *average* CO_2 concentrations for the intake charge are 1.4 % (for fully open) and 0.05% for the fully shut case (0.5% for the identification data). These results tend to confirm the bias hypothesis stated above. The system gains for NOx are affected only slightly and the torque response is almost the same.

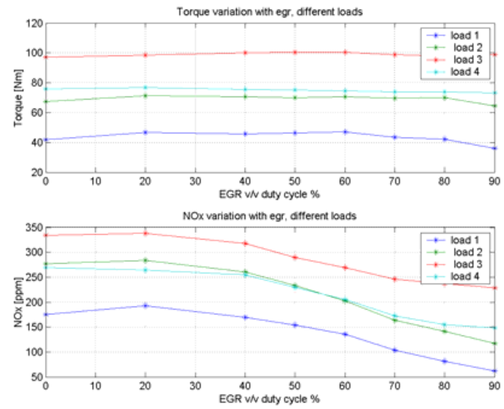

Fig. 7 Torque and NOx variation with EGR v/v duty cycle, 1800 RPM

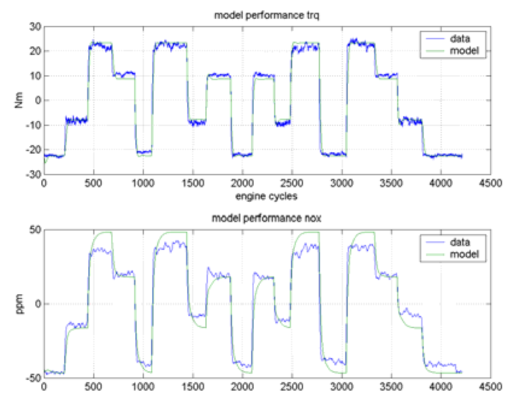

Fig. 8 Torque and NOx prediction, EGR closed

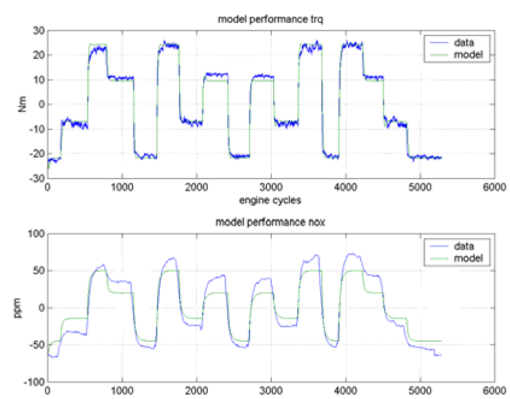

Fig. 9 Torque and NOx prediction, EGR open

4. STATE ESTIMATION

Using the model described in section 3, observers may be designed using states whose measurements are available. For our case, Torque and NOx are the outputs of direct interest. However, these measurements are currently not directly available. Instead MAP (P1) and maf are very common on production engines. Therefore, it will be interesting to investigate if Torque and NOx can be predicted using these measurements. A steady-state Kalman filter was designed and tested using the another validation data-set (same operating conditions but different input profile). The performance of Kalman filter is shown in figures 10-11.

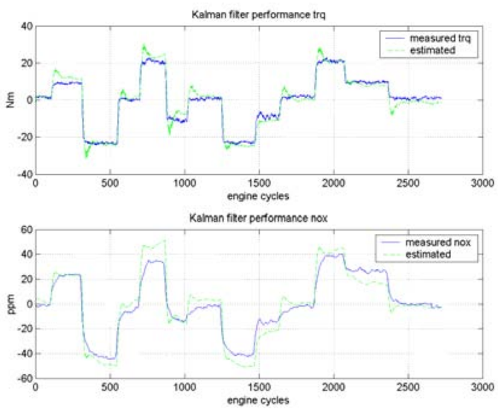

Fig. 10 Kalman Filter performance - Torque and NOx

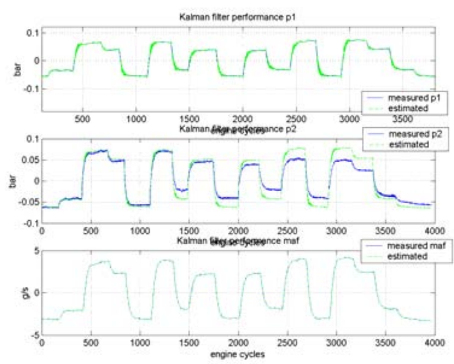

Fig. 11 Kalman Filter performance - *p1*, *p2* and *maf*

5. CONCLUSION

In conclusion, an existing air-loop model structure for common-rail Diesel engines was extended to predict Torque and NOx dynamics in response to combined excitations in fuel quantity and timing. This model structure was linearized and identified at a certain engine operating point. The validity of this structure was demonstrated. The effect of parameter variations in the form of EGR valve position was analyzed and it was shown that the linearized dynamics is not affected much. A Kalman Filter was designed based on this grey-box model structure using manifold pressure and mass air flow as available measurements. It was demonstated that Torque and NOx can be accurately predicted using these measurements.

NOMENCLATURE AND GLOSSARY

NOx Oxides of Nitrogen
EGR Exhaust Gas Recirculation
VGT Variable Geometry Turbcharging
MBT Mean Best Torque
ATDC After TDC
MAP, P1 Manifold pressure, intake manifold
P2 Exhaust manifold pressure
MAF mass air flow, compressor flow rate
PW commanded fuel pulse-width
SOI start of injection relative to TDC

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