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Exhaust pressure LPV observer for turbocharged diesel engine on-board diagnosis

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Abstract: This paper deals with the estimation of the exhaust manifold pressure for a truck diesel engine equipped with a turbocharger. The knowledge of this variable is essential in order to fulfill functions such as the exhaust brake control or on-board diagnosis (OBD) of anti-pollution systems. However, while in most cases the pressure is directly measured, the sensor may encounter failures in some specific operating conditions. Its estimation is then of great interest for diagnosis and fault tolerant control objectives. Based on mean value models of the turbocharger and the exhaust manifold, a Linear Parameter Varying (LPV) polytopic observer is designed to provide an estimation of the pressure. The merits of this solution are illustrated with the high-fidelity professional simulator GT-POWER.

Keywords: LPV observer, automotive systems, diagnosis

1. INTRODUCTION

In most automotive engines, the exhaust manifold pressure is directly measured by a sensor. However, some problems have been reported concerning the robustness of the sensor. In fact, in addition to its high cost, it must face strong pressure oscillations and high temperature conditions. Indeed, these conditions have accused for example tube clogging problems to the sensor. Therefore it is not reliable in all the operating conditions of the engine. Although this pressure information is difficult to get, it is essential for engine control. Among others, it is used to control the exhaust pressure with the exhaust flap in order to get an engine brake and to estimate the burned fraction to ensure an on-board diagnosis (OBD) for the anti-pollution system. Since it is mandatory to propose an OBD solution (Mohammadpour et al., 2012), its estimation is then of great interest for diagnosis and fault tolerant control objectives.

To overcome such problems, model-based estimation represents an efficient alternative. Therefore, several authors have proposed different methods to estimate the exhaust manifold pressure. One can categorize them in two types: nonlinear observer-based approaches (Fredriksson and Egardt, 2002) and inverse model approaches (Castillo et al., 2013; Olin, 2008; Yue-Yun Wang and Hashara, 2010). The latter estimators propose to directly estimate this variable from the information of the exhaust air mass flow through the orifice flow equation or from the turbine’s data-maps.

In (Fredriksson and Egardt, 2002), the authors proposed a generalized Luenberger observer based on mean value models of the intake and exhaust manifolds, the turbocharger and engine dynamics which leads to a fourth order nonlinear observer.

In this paper, we propose for the first time, up to the authors’ knowledge, a Linear Parameter Varying (LPV) observer based on mean value models of the turbocharger and the exhaust manifold to estimate the pressure. Since the equipment of the engine under consideration, and thus the measurement at our disposal, are not the same as in (Fredriksson and Egardt, 2002), it leads to a second order LPV observer. Besides, our method encompasses a systematic calibration procedure, contrary to the previous one where tuning the observer parameters is not an easy task. Moreover, the observer is proposed considering two different models for the turbine mass flow rate: a standard orifice equation, and a new identified black-box model. The merits of the developed solution are then validated on a high industrial complex simulator with realistic engine cycles.
2. MEAN VALUE MODEL OF THE ENGINE

The architecture of the diesel engine under consideration is depicted in Fig. 1. This engine is a medium-duty 4-cylinders 5L diesel one equipped with a Variable Geometry Turbocharger (VGT) and a Exhaust Gas Recirculation (EGR) loop. In this section and in all the paper, we will consider \( \dot{m}_3 \) the total air mass inside the volume \( V_3 \).

By derivating this equation, one obtains:

\[
\dot{P}_3 = \frac{\dot{m}_3 RT_3}{V_3} + \frac{m_3 R \dot{T}_3}{V_3} \tag{2}
\]

where \( \dot{m}_3 \) represents the mass rate of gas flowing through the exhaust manifold and can be expressed, from a balance equation, \( \dot{m}_3 = D_{asp} + D_f - D_{egr} \). Besides, assuming that the temperature varies slowly in comparison to \( \dot{P}_3 \), we consider \( \dot{T}_3 \approx 0 \) and (2) becomes:

\[
\dot{P}_3 = \frac{RT_3}{V_3} \left( D_{asp} + D_f - D_{egr} - D_t \right) \tag{3}
\]

In (3), the mass flow rates \( D_f \) and \( D_{egr} \) are known input variables, and the air mass flow aspired by the cylinders can be expressed as:

\[
D_{asp} = \frac{\eta_v V_{cyl} N_{eng}}{RT_2^{120}} P_2 \tag{4}
\]

where \( \eta_v \) is the volumetric efficiency defined as the ratio between the actual volume flow rate of air and the theoretical volume flow rate of air displaced by the pistons.

It is in general given by a map in function of the engine speed and the intake manifold pressure: \( \eta_v(N_{eng}, P_2) \). See (Isermann, 2014) for a more detailed model and about the efficiency protocol measurement. The mass flow rate \( D_t \) will be expressed in Section 2.3.

2.2 Turbocharger dynamics

Located just after the EGR loop and the exhaust manifold, the turbocharger is a combination of a turbine and a compressor. The main function of the turbocharger is to increase the air density in the intake manifold by recovering energy from the exhaust gases. Its secondary functions are: increase the exhaust pressure \( P_3 \) in order to drive the EGR flow or allow engine brake.

There are several studies proposing a model of the turbocharger. Some are control-oriented such as (Salehi et al., 2013) or modeling-oriented (Jung et al., 2002; Isermann,

---

Table 1. Nomenclature

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N_{eng} )</td>
<td>Engine speed</td>
<td>rpm</td>
</tr>
<tr>
<td>( \omega_{tc} )</td>
<td>Rotor speed of the turbocharger</td>
<td>rad.s(^{-1})</td>
</tr>
<tr>
<td>( J_{tc} )</td>
<td>Shaft moment of inertia of the turbocharger</td>
<td>kg.m(^2)</td>
</tr>
<tr>
<td>( P )</td>
<td>Power</td>
<td>W</td>
</tr>
<tr>
<td>( T )</td>
<td>Temperature of a subsystem</td>
<td>K</td>
</tr>
<tr>
<td>( P )</td>
<td>Pressure of a subsystem</td>
<td>Pa</td>
</tr>
<tr>
<td>( c_p )</td>
<td>Specific heat</td>
<td>J.(kg)^{-1}.K(^{-1})</td>
</tr>
<tr>
<td>( R )</td>
<td>Ideal gas constant for the air</td>
<td>J.(kg)^{-1}.K(^{-1})</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>Specific heat ratio</td>
<td>-</td>
</tr>
<tr>
<td>( D )</td>
<td>Mass flow rate</td>
<td>kg.s(^{-1})</td>
</tr>
</tbody>
</table>

Subscript

1. Upstream the compressor
2. Inside the intake manifold
3. Inside the exhaust manifold
4. Downstream the turbine
c. Related to the compressor
t. Related to the turbine
egr. Related to the EGR loop
f. Related to the fuel

---

1 www.gtiisoft.com
From the mechanical power balance, one can obtain the rotor speed dynamic of the turbocharger:

$$\frac{1}{2}J_{tc}(\omega_{tc}^2) = \mathcal{P}_t - \mathcal{P}_c$$

(5)

where \(\mathcal{P}_c\) and \(\mathcal{P}_t\) are respectively the compressor and turbine powers.

Now, from the formula of the isentropic compression, the consideration of heat loses through the efficiency maps and the first law of thermodynamics, these powers can be expressed as:

$$\mathcal{P}_c = \frac{1}{\eta_c}T_1c_{p1}D_c \left( \frac{P_2}{P_1} \right)^{\frac{\gamma_1-1}{\gamma_1}} - 1$$

(6)

$$\mathcal{P}_t = \eta_tT_3c_{p3}D_t \left( 1 - \left( \frac{P_4}{P_3} \right)^{\frac{\gamma_3-1}{\gamma_3}} \right)$$

(7)

As mentioned in (Isermann, 2014), one can consider the parameters \(\gamma_1, \gamma_3, c_{p1}, c_{p3}\) and \(R\) as constant. In addition, due to their low dispersion, we assume that \(\gamma_1 = \gamma_3 = \gamma\).

The efficiencies \(\eta_c\) and \(\eta_t\) are given by interpolated maps from data provided by the manufacturer of the turbocharger.

### 2.3 Turbine flow modeling

Since mass flow rate passing through the turbine \(D_t\) is not measured, one can use the classical orifice flow equation to model the mass flow rate of the turbine (Moulin, 2010):

$$D_t = A(u_{vgt}) \frac{P_3}{\sqrt{RT_3}} \Psi \left( \frac{P_4}{P_3} \right)$$

(8)

$$\Psi \left( \frac{P_4}{P_3} \right) = \sqrt{\frac{2\gamma}{\gamma - 1} \left( \Pi^2 - \Pi^{\frac{\gamma+1}{\gamma}} \right)}$$

(9)

where \(\Pi\) represents the pressure ratio in normal and critical conditions, which is defined by:

$$\Pi = \max \left( \frac{P_4}{P_3}, \frac{2\gamma}{\gamma + 1} \right)$$

(10)

In our study, the effective area \(A(u_{vgt})\) is identified as a third order polynomial function of the command \(u_{vgt}\).

In the sequel, the following fit performance index will be used:

$$FIT = 1 - \frac{\|D_t - D_t(Model)\|_2}{\|D_t - \text{mean}(D_t)\|_2}$$

(11)

The results of this model for \(D_t\) are depicted in Fig. 3 and compared with the reference data provided by GT-POWER.

Even if the model seems to be good, the results could be improved especially in the last hundreds seconds. To do so, a Hammerstein-Wiener (HW) model has been identified. A

\*In this study the mechanical friction is neglected but can be easily added via a constant efficiency

$$\hat{\omega}_{tc} = \frac{2}{J_{tc}} \eta_tT_3c_{p3}D_t \left( 1 - \left( \frac{P_4}{P_3} \right)^{\frac{\gamma_3-1}{\gamma_3}} \right) - \frac{2}{J_{tc}} \frac{1}{\eta_c}T_1c_{p1}D_c \left( \frac{P_2}{P_1} \right)^{\frac{\gamma_1-1}{\gamma_1}} - 1$$

(12)

$$\hat{\mathcal{P}}_3 = \frac{RT_3}{V_3} (\mathcal{D}_{asp} + \mathcal{D}_f - \mathcal{D}_{egr} - \mathcal{D}_t)$$

where \(\mathcal{D}_t\), for comparison purpose, will be calculated using the two models defined in the previous Section 2.3: the orifice flow equations (8)-(10) and the identified Hammerstein-Wiener model.

### 3. OBSERVER DESIGN

To take into account the nonlinearities of the system described in Section 2.4, a quasi-LPV approach is considered to design an observer for the exhaust manifold pressure \(\mathcal{P}_3\).
3.1 LPV modeling

Let denote \([x_1 \ x_2]^T = [\omega^2_{tc} \ \rho_3]^T\) the state vector. We choose to transform the nonlinear system described by (12) into the following quasi-LPV form:

\[
\begin{bmatrix}
\dot{x}_1 \\
\dot{x}_2 \\
\end{bmatrix} = 
\begin{bmatrix}
0 & \rho_1 \\
0 & \rho_2 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
\end{bmatrix} + 
\begin{bmatrix}
1 \\
0 \\
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2 \\
\end{bmatrix}
\]

\[
= A(\rho)x + Bu \\
y = [1 \ 0]x = Cx
\]

(13)

with, in the case where \(D_t\) is given by (8)-(10),

\[
\begin{align*}
\rho_1 &= \eta_t T_3 c_{\rho 3} \left(1 - \left(\frac{P_4}{P_3}\right)^{\gamma - 1}\right) A(u_{e,yt}) \frac{1}{\sqrt{JT_3}} \Psi \left(\frac{P_4}{P_3}\right) \frac{2}{J_{tc}} \\
\rho_2 &= -A(u_{e,yt}) \frac{1}{\sqrt{JT_3}} \Psi \left(\frac{P_4}{P_3}\right) \frac{T_3 R}{V_3} \\
u_1 &= \frac{2}{J_{tc}} P_c \\
u_2 &= \frac{T_3 R}{V_3} (D_{asp} + D_f - D_{egr})
\end{align*}
\]

(14)

It is worth noting that (13) is a quasi-LPV model since \(\rho_1\) and \(\rho_2\) depend on \(x_2 = P_3\). Therefore, in the LPV observer form, \(\rho_1\) and \(\rho_2\) will be computed on-line using the estimated pressure \(\hat{P}_3\).

3.2 Problem formulation

For the synthesis problem, consider the following LPV system:

\[
\begin{align*}
\dot{x} &= A(\rho)x + Bu + Ew \\
y &= Cx; \quad z = Czc
\end{align*}
\]

(15)

where \(x \in \mathbb{R}^{n_x}\) is the state vector, \(u \in \mathbb{R}^{n_u}\) the known input vector, \(y \in \mathbb{R}^{n_y}\) the measure vector, \(z \in \mathbb{R}^{n_z}\) the variable to estimate and \(w \in \mathbb{R}^{n_w}\) represents additive uncertainties that we want to attenuate. The parameter vector \(\rho\) consists of \(N\) varying parameters \([\rho_1 \ldots \rho_N]^T\) where each component \(\rho_i \in [\rho_{i L}, \rho_{i U}]\).

As introduced in (Apkarian et al., 1995), if the parameter dependence of \(A(\rho)\) is affine (as in (13)) and if the parameter vector \(\rho\) varies in a polytope \(\mathcal{T}\) of \(2^N\) vertices such that,

\[
\begin{align*}
\rho &\in \mathcal{T} := Co\{\omega_1, \omega_2, \ldots, \omega_{2^N}\} \\
\omega_i &\in \{(\omega_1, \omega_2, \ldots, \omega_{2^N}) | \omega_i \in [\rho_{i L}, \rho_{i U}]\}
\end{align*}
\]

(16)

then, the matrix \(A(\rho)\) can be transformed into a convex interpolation such that:

\[
A(\rho) = \sum_{i=1}^{2^N} \mu_i(\rho) A_i; \quad i = 0, \sum_{i=1}^{2^N} \mu_i(\rho) = 1
\]

(17)

where the matrices \(A_i = A(\omega_i)\) are time-invariant and correspond to the image of a vertex of \(\mathcal{T}\).

In our case, with 2 parameters bounded in \([\rho_{1 U}, \rho_{1 L}]\) and \([\rho_{2 U}, \rho_{2 L}]\), (see (Bara et al., 2001) for the general case) the corresponding polytope is:

\[
\mathcal{T} = Co\{\omega_1, \omega_2, \omega_{2^3}, \omega_4\} = Co\{[\rho_1, \rho_2], ([\rho_1, \rho_2], [\rho_{1 U}, \rho_{2 U}]), ([\rho_1, \rho_2], [\rho_{2 L}, \rho_{2 U}])\}
\]

(18)

The objective is to estimate the state vector \(x\) of (15) while minimizing a \(H_\infty\) criterion with respect to disturbance terms. The proposed polytopic LPV observer has the following structure:

\[
\dot{\hat{x}} = \sum_{i=1}^{4} (\mu_i(\hat{\rho})(A_i \hat{x} + L_i (y - \hat{y}))) + Bu
\]

\[
\hat{y} = C \hat{x}; \quad \hat{z} = C_z \hat{x}
\]

(19)

where \(L_i\) are unknown matrices to be determined.

Let \(T_{wuc}\) denote the closed-loop transfer function from \(w\) to the state error estimation \(e_z = z - \hat{z}\). The objective is to design an observer (19) such that:

- the poles of \(T_{wuc}\) are in a desired region to ensure both convergence performance and stability
- the \(H_\infty\) norm of \(T_{wuc}\) is minimized

3.3 Synthesis

First let us notice that, even if the parameter vector is using estimated state variables (due to the quasi-LPV model), we assume here that \(\hat{\rho} = \rho\) for the synthesis of the observer (19). As presented in (Heemels et al., 2010), a robustness study with respect to uncertainty on the scheduling variables could be done in the future.

Proposition 1. Given (15)-(17) and the observer (19). If there exists symmetric positive-definite matrix \(P\) and matrices \(Y_i\) such that:

\[
PA_i - Y_i C + A_i^T P - C^T Y_i^T + 2\alpha P < 0
\]

\[
\begin{bmatrix}
-rP \\
* \\
-\frac{e_r}{P} \\
-\frac{e_r}{P}
\end{bmatrix} < 0
\]

\[
\sin(\theta)(PA_i - Y_i C + A_i^T P - C^T Y_i^T) \cos(\theta)(PA_i - Y_i C + A_i^T P - C^T Y_i^T) < 0
\]

\[
\min_{\gamma_\infty} \gamma_\infty \quad \text{s.t.} \\
\begin{bmatrix}
PA_i - Y_i C + A_i^T P - C^T Y_i^T \\
E \quad PC_i^T
\end{bmatrix} \begin{bmatrix}
* \\
* -\gamma_\infty I \\
* -\gamma_\infty I
\end{bmatrix} < 0
\]

(20)

(21)

(22)

(23)

Then the poles of the transfer function \(T_{wuc}\) are in the considered area depicted in Fig. 4 and its \(H_\infty\) norm is minimized by \(\gamma_\infty\). Besides, the observer gains \(L_i\) are deduced as \(L_i = P^{-1}Y_i\).

Proof: The proof follows the steps as described in (Chilali and Gahinet, 1996). If a single Lyapunov function can be found for all the vertices of the polytopic system, the derived LPV observer stabilizes the LPV system for all possible variations of the scheduling parameters in the bounded set.

Applying Proposition 1 to system (13)-(14) for: \(\alpha = 4; \quad \theta = \pi/6; \quad r = 80\) associated with \(E = I_2\) and \(C_z = [0 \ 1]\), gives the roots locus depicted in Fig. 4 and \(\gamma_\infty = 0.8902\).
4. SIMULATION RESULTS

The validation will be based on two standard types of test:

- The World Harmonized Stationary Cycle (WHSC), which is a succession of stationary points in the engine speed and torque.
- The World Harmonized Transient Cycle (WHTC), which is a transient test based on the pattern of heavy duty commercial vehicles.

These two cycles are used as inputs for the GT-POWER simulator, then the needed data are collected to feed the observer (19) of the system (13). The scheme presented in Fig. 5, summarizes the considered simulation tests. In addition to both cycles, we will compare the two different models for $D_t$ defined in Section 2.3.

For comparison purpose, let us define a performance estimation criterion as the normalized root mean square $NRMS$:

$$NRMS = \sqrt{\frac{1}{N_e} \sum_{n=1}^{N_e} |\hat{P}_3(n) - P_3(n)|^2}$$

where $N_e$ is the number of data points.

The performance results for the different cases and scenarios are summarized in Table 2.

4.1 Case 1: $D_t$ defined by the orifice equations (8)-(10)

The results obtained for the two scenarios (WHSC/WHTC) in the case where $D_t$ is defined by the orifice flow equations (8)-(10), are respectively presented in Fig. 6 and 7. The observer manages to follow the variations of the pressure with a reasonable error for both scenarios.

4.2 Case 2: $D_t$ defined by HW model

In this case $D_t$ is defined by the Hammerstein-Wiener model identified in Section 2.3. The results for the WHSC cycle are depicted in Fig. 8 and for the WHTC in Fig. 9. One can observe that the estimation is improved and, for some stationary points, the error is close to zero. This is confirmed by the NRMS results shown in Table 2.

5. CONCLUSION

In this paper, we have designed a LPV observer in order to estimate the exhaust manifold pressure of a turbocharged diesel engine. In Section 2, a mean value model of the
turbocharger and pressure dynamics has been developed. In this section, we also proposed two models of the turbine mass flow rate. A standard model from the orifice flow equations and a Hammerstein-Wiener model. Then, in Section 3, thanks to the LPV framework, a polytopic LPV observer has been designed to estimate the state space vector of the system. It is worth mentioning that this quasi-LPV observer internally depends on the estimated state variable $\hat{x}_2$, and further works must be performed to study the effects of the uncertainties in the parameters due to the estimation of $P_3$ as investigated in (Heemels et al., 2010).

In Section 4, the observer has been tested in a high-fidelity simulator in GT-POWER in different scenarios. It has been shown that the observer has a low estimation error in every tested scenarios. As shown in Table 2, the HW model has the best estimation results. This observation could be expected because it has been established in Section 2.3 that this model has the best fit. However, this model seems to be too complex for a real-time implementation. Then, in practical implementations, the orifice flow equations may be preferred.

Even if the estimation results are good, it appears that the estimation error is more important at certain points. It has been established in Section 4.1 and 4.2 that the modeling improvement on the variable $D_t$ corrects most of these errors. However, some still remain. To attenuate them, one can investigate in further works the constant assumption made on the thermal coefficients, improve the precision of the efficiency maps of the turbocharger or use the pressure measurement just after the compressor instead of the intake manifold one to compute the compressor power (6).

REFERENCES


