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

Donatien Dubuc, Olivier Sename, Delphine Bresch-Pietri, Adrien Halle, Christophe Gauthier

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

Donatien Dubuc *,** **Olivier Sename** **
Delphine Bresch-Pietri *** **Adrien Halle** *
Christophe Gauthier ****

* *Volvo Group, Saint Priest, France*
(e-mail: donatien.dubuc, adrien.halle@volvo.com)
** *Univ. Grenoble Alpes, CNRS, Grenoble INP, GIPSA-lab, 38000 Grenoble, France*
(e-mail: olivier.sename@gipsa-lab.fr)
*** *MINES Paristech, PSL Research University, CAS - Centre Automatique et Systèmes*
(e-mail: delphine.bresch-pietri@mines-paristech.fr)
**** *JTEKT Europe, ZI du Broteau, BP1, 69540 Irigny, France*
(e-mail: cgauthier2000@yahoo.fr)

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 Haskara, 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.

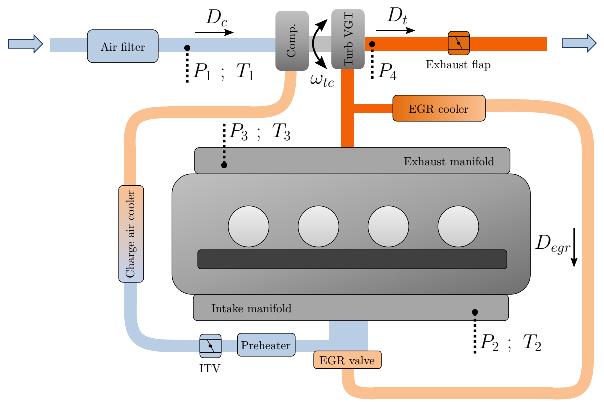

Fig. 1. Scheme of the air path in the considered engine

The paper is organized as follows. In Section 2, a mean value model is presented. In Section 3, based on this model, a LPV polytopic observer is designed to estimate the exhaust pressure. The observer is synthesized in order to minimize a H_∞ criterion associated with a pole placement by Linear Matrix Inequalities (LMIs) regions. Then, in Section 4, the performances of this observer are illustrated in a realistic simulator designed with GT-POWER. Finally, conclusions are stated in Section 5.

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 use data provided by a high-fidelity simulator designed with GT-POWER [1] . This software, developed by Gamma Technology, consists in a set of simulation libraries for analyzing the engine behavior and is largely used in the automotive industry. Therefore all the reference data are provided by this simulator.

The measurements considered for this study are: D_c, D_{egr}, P_1, T_1, P_2, T_2, T_3, P_4 and ω_{tc}. These variables are typically measured or estimated in the automotive industry. Their nomenclature is given in Table 1.

In the following, the exhaust manifold and turbocharger dynamics are modeled using a mean value approach such as in (Isermann, 2014; Moulin, 2010).

2.1 Exhaust manifold dynamics

Located just after the engine block, this manifold permits to collect all the gases from the cylinders into one pipe which is directly connected to the turbine.

The exhaust manifold can be represented as an open thermodynamical system, where the quantity of gas can increase or decrease. It is called a "filling and emptying" system. Inside this volume, the ideal gas law can be applied and the pressure P_3 can be expressed as:

$$P_3 = \frac{m_3 R T_3}{V_3} \tag{1}$$

[1] www.gtisoft.com

Table 1. Nomenclature

Notation	Description	Unit
N_{eng}	Engine speed	rpm
ω_{tc}	Rotor speed of the turbocharger	rad.s^{-1}
J_{tc}	Shaft moment of inertia of the turbocharger	kg.m^2
$\mathcal{P}$	Power	W
T	Temperature of a subsystem	K
P	Pressure of a subsystem	Pa
c_p	Specific heat	J.kg^{-1}.K^{-1}
R	Ideal gas constant for the air	J.kg^{-1}.K^{-1}
γ	Specific heat ratio	-
D	Mass flow rate	kg.s^{-1}
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	

where m_3 is the total air mass inside the volume V_3.

By derivating this equation, one obtains:

$$\dot{P}_3 = \frac{\dot{m}_3 R T_3}{V_3} + \frac{m_3 R \dot{T}_3}{V_3} \tag{2}$$

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 P_3, we consider $\dot{T}_3 \simeq 0$ and (2) becomes:

$$\dot{P}_3 = \frac{R T_3}{V_3} \left(D_{asp} + D_f - D_{egr} - D_t \right) \tag{3}$$

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:

$$D_{asp} = \frac{\eta_v V_{cyl} N_{eng}}{R T_2 120} P_2 \tag{4}$$

where η_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, 2014). From the mechanical power balance, one can obtain the rotor speed dynamic of the turbocharger [2] :

$$\frac{1}{2}J_{tc}(\dot{\omega_{tc}^2}) = \mathcal{P}_t - \mathcal{P}_c \tag{5}$$

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:

$$\mathcal{P}_c = \frac{1}{\eta_c}T_1 c_{p1} D_c \left(\left(\frac{P_2}{P_1}\right)^{\frac{\gamma_1 - 1}{\gamma_1}} - 1 \right) \tag{6}$$

$$\mathcal{P}_t = \eta_t T_3 c_{p3} D_t \left(1 - \left(\frac{P_4}{P_3}\right)^{\frac{\gamma_3 - 1}{\gamma_3}} \right) \tag{7}$$

As mentioned in (Isermann, 2014), one can consider the parameters γ_1, γ_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 η_c and η_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):

$$D_t = A(u_{vgt})\frac{P_3}{\sqrt{RT_3}}\Psi\left(\frac{P_4}{P_3}\right) \tag{8}$$

$$\Psi\left(\frac{P_4}{P_3}\right) = \sqrt{\frac{2\gamma}{\gamma - 1}\left(\Pi^{\frac{2}{\gamma}} - \Pi^{\frac{\gamma+1}{\gamma}}\right)} \tag{9}$$

where Π represents the pressure ratio in normal and critical conditions, which is defined by:

$$\Pi = \max\left(\frac{P_4}{P_3}, \left(\frac{2\gamma}{\gamma+1}\right)^{\frac{\gamma}{\gamma-1}}\right) \tag{10}$$

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:

$$FIT = 1 - \frac{\|D_t - D_t(Model)\|_2}{\|D_t - \mathrm{mean}(D_t)\|_2} \tag{11}$$

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

[2] In this study the mechanical friction is neglected but can be easily added via a constant efficiency

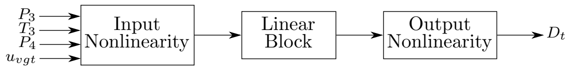

Fig. 2. Hammerstein-Wiener model block diagram

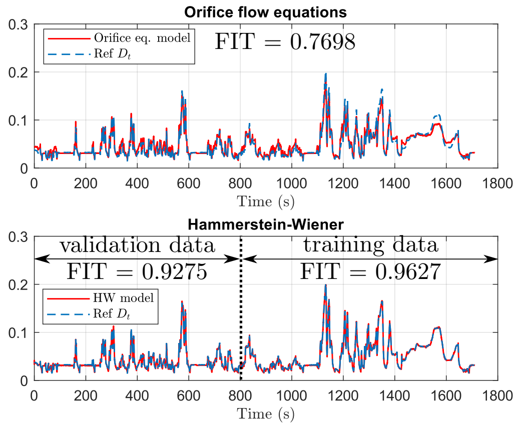

Fig. 3. Turbine mass flow rate obtained with orifice flow equations (8)-(10) and a Hammerstein-Wiener model (FIT computed with (11))

HW model is a combination of three blocks as depicted in Fig. 2: a static input nonlinearity, a linear dynamic system, and a static output nonlinearity. For more information about this model see for example (Zhu, 2002). In our case, sigmoid networks have been chosen for the input and output nonlinear functions, which can be defined as a sum of weighted sigmoid functions $(e^z + 1)^{-1}$. The linear system is a polynomial model with 1 zero, 2 poles with a delay set to 1. The identification was performed with the System Identification Toolbox of MATLAB using the same inputs as the previous model (i.e: P_3, T_3, P_4 and u_{vgt} as in Fig. 2).

This black-box model improves significantly the fit of the data (Fig. 3).

2.4 Considered system

Finally, combining equations (3), (4), (5), (6) and (7), the following nonlinear differential equations are obtained:

$$\begin{aligned} \dot{\omega_{tc}^2} &= \frac{2}{J_{tc}}\eta_t T_3 c_{p3} D_t \left(1 - \left(\frac{P_4}{P_3}\right)^{\frac{\gamma_3-1}{\gamma_3}}\right) \\ &\quad - \frac{2}{J_{tc}}\frac{1}{\eta_c}T_1 c_{p1} D_c \left(\left(\frac{P_2}{P_1}\right)^{\frac{\gamma_1-1}{\gamma_1}} - 1\right) \\ \dot{P_3} &= \frac{RT_3}{V_3}\left(D_{asp} + D_f - D_{egr} - D_t\right) \end{aligned} \tag{12}$$

where 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 P_3.

3.1 LPV modeling

Let denote $[x_1 \;\; x_2]^T = [\omega_{tc}^2 \;\; P_3]^T$ the state vector. We choose to transform the nonlinear system described by (12) into the following quasi-LPV form:

$$\begin{aligned} \begin{bmatrix} \dot{x_1} \\ \dot{x_2} \end{bmatrix} &= \begin{bmatrix} 0 & \rho_1 \\ 0 & \rho_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\ &= A(\rho)x + Bu \\ y &= [1 \;\; 0]\, x = Cx \end{aligned} \tag{13}$$

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

$$\begin{aligned} \rho_1 &= \eta_t T_3 c_{p3} \left(1 - \left(\frac{P_4}{P_3}\right)^{\frac{\gamma-1}{\gamma}}\right) A(u_{vgt}) \frac{1}{\sqrt{RT_3}} \Psi\left(\frac{P_4}{P_3}\right) \frac{2}{J_{tc}} \\ \rho_2 &= -A(u_{vgt}) \frac{1}{\sqrt{RT_3}} \Psi\left(\frac{P_4}{P_3}\right) \frac{T_3 R}{V_3} \\ u_1 &= -\frac{2}{J_{tc}} \mathcal{P}_c \;\; ; \;\; u_2 = \frac{T_3 R}{V_3} \left(D_{asp} + D_f - D_{egr}\right) \end{aligned} \tag{14}$$

It is worth noting that (13) is a quasi-LPV model since ρ_1 and ρ_2 depend on $x_2 = P_3$. Therefore, in the LPV observer form, ρ_1 and ρ_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:

$$\begin{aligned} \dot{x} &= A(\rho)x + Bu + Ew \\ y &= Cx; \quad z = C_z x \end{aligned} \tag{15}$$

where $x \in R^{n_x}$ is the state vector, $u \in R^{n_u}$ the known input vector, $y \in R^{n_y}$ the measure vector, $z \in R^{n_z}$ the variable to estimate and $w \in R^{n_w}$ represents additive uncertainties that we want to attenuate. The parameter vector ρ consists of N varying parameters $[\rho_1 \;\; ... \;\; \rho_N]^T$ where each component $\rho_i \in [\underline{\rho_i}, \overline{\rho_i}]$.

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

$$\begin{aligned} \rho &\in \Upsilon := Co\{\omega_1, \omega_2, ..., \omega_{2^N}\} \\ \omega_i &\in \left\{(\varpi_1, \varpi_2, ..., \varpi_N) \mid \varpi_i \in \{\underline{\rho_i}, \overline{\rho_i}\}\right\} \end{aligned} \tag{16}$$

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

$$A(\rho) = \sum_{i=1}^{2^N} \mu_i(\rho) A_i, \quad \mu_i(\rho) \geq 0, \quad \sum_{i=1}^{2^N} \mu_i(\rho) = 1 \tag{17}$$

where the matrices $A_i = A(\omega_i)$ are time-invariant and correspond to the image of a vertex of Υ.

In our case, with 2 parameters bounded in $[\underline{\rho_1}, \overline{\rho_1}]$ and $[\underline{\rho_2}, \overline{\rho_2}]$, (see (Bara et al., 2001) for the general case) the corresponding polytope is:

$$\begin{aligned} \Upsilon &= Co\{\omega_1, \omega_2, \omega_3, \omega_4\} \\ &= Co\{(\underline{\rho_1}, \underline{\rho_2}), (\underline{\rho_1}, \overline{\rho_2}), (\overline{\rho_1}, \underline{\rho_2}), (\overline{\rho_1}, \overline{\rho_2})\} \end{aligned} \tag{18}$$

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

$$\begin{aligned} \dot{\hat{x}} &= \sum_{i=1}^{4} \left(\mu_i(\hat{\rho})(A_i \hat{x} + L_i(y - \hat{y}))\right) + Bu \\ \hat{y} &= C\hat{x}; \quad \hat{z} = C_z \hat{x} \end{aligned} \tag{19}$$

where L_i are unknown matrices to be determined.

Let T_{we_z} 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_{we_z} are in a desired region to ensure both convergence performance and stability
- the H_∞ norm of T_{we_z} 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:

$$PA_i - Y_i C + A_i^T P - C^T Y_i^T + 2\alpha P < 0 \tag{20}$$

$$\begin{bmatrix} -rP & PA_i - Y_i C \\ * & -rP \end{bmatrix} < 0 \tag{21}$$

$$\begin{bmatrix} \sin\theta(PA_i - Y_i C + A_i^T P - C^T Y_i^T) & \cos\theta(PA_i - Y_i C - A_i^T P + C^T Y_i^T) \\ * & \sin\theta(PA_i - Y_i C + A_i^T P - C^T Y_i^T) \end{bmatrix} < 0 \tag{22}$$

$$\begin{aligned} &\min \;\; \gamma_\infty \\ &s.t \begin{bmatrix} PA_i - Y_i C + A_i^T P - C^T Y_i^T & E & PC_z^T \\ * & -\gamma_\infty I & 0 \\ * & * & -\gamma_\infty I \end{bmatrix} < 0 \end{aligned} \tag{23}$$

for all $i = 1, 2, \ldots, 2^N$.

Then the poles of the transfer function T_{we_z} are in the considered area depicted in Fig. 4 and its H_∞ norm is minimized by γ_∞. 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: $\alpha = 4$; $\theta = \pi/6$; $r = 80$ associated with $E = I_2$ and $C_z = [0 \;\; 1]$, gives the roots locus depicted in Fig. 4 and $\gamma_\infty = 0.8902$.

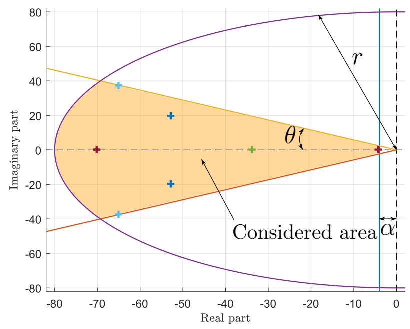

Fig. 4. Roots locus of T_{we_z}

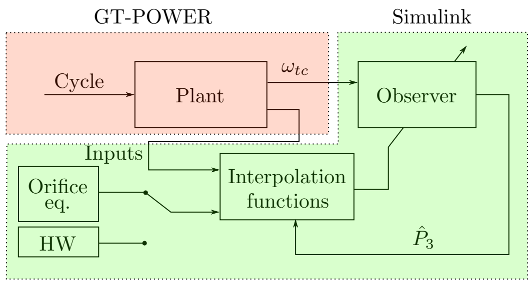

Fig. 5. Scheme of the simulation tests

The observer gains at the 4 vertices of the polytope are:

$$L_1 = [70.60 \quad 1.10]^T \ , \quad L_2 = [96.79 \quad 2.01]^T$$
$$L_3 = [70.60 \quad 1.93]^T \ , \quad L_4 = [101.91 \quad 2.36]^T$$

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 $NRMS$:

$$NRMS = \frac{\sqrt{\frac{1}{N_e}\sum_{n=1}^{N_e}|\hat{P}_3(n) - P_3(n)|^2}}{\max_{n=1,N_e} P_3(n) - \min_{n=1,N_e} P_3(n)} \qquad (24)$$

where Ne 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

Table 2. $NRMS$ obtained for the different cases

Cycle \ Model for D_t	**Orifice eq.**	**HW**
WHSC	0.0610	0.0255
WHTC	0.0499	0.0189

(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.

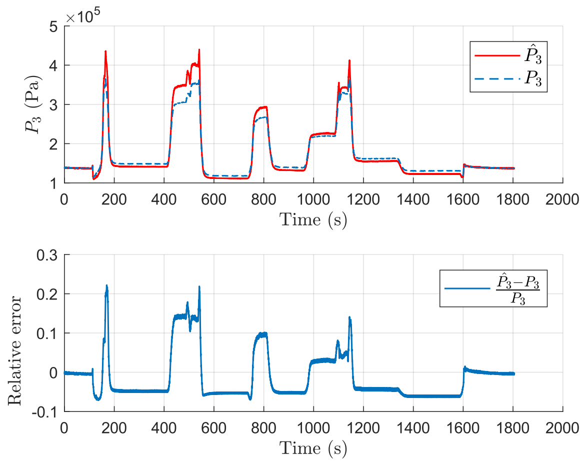

Fig. 6. WHSC cycle with D_t defined by (8)-(10)

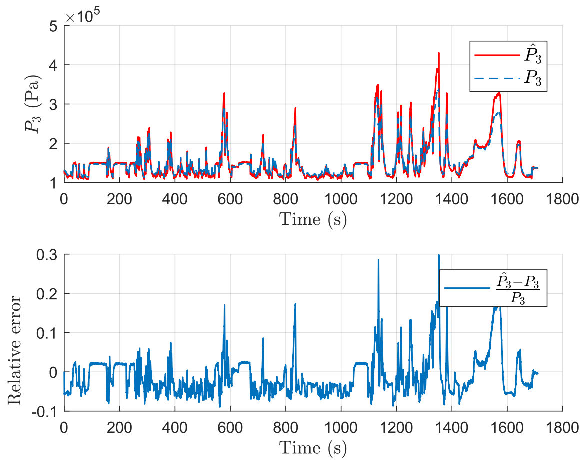

Fig. 7. WHTC cycle with D_t defined by (8)-(10)

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

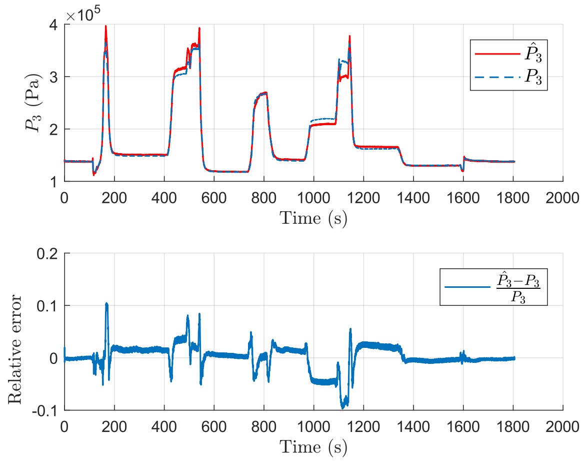

Fig. 8. WHSC cycle with D_t defined by the Hammerstein-Wiener model

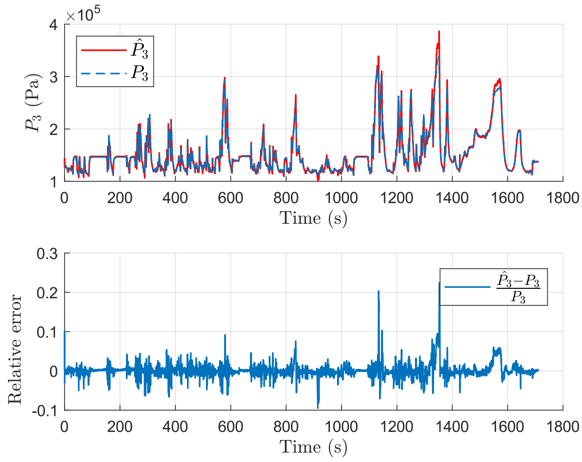

Fig. 9. WHTC cycle with D_t defined by the Hammerstein-Wiener model

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

Apkarian, P., Gahinet, P., and Becker, G. (1995). Self-scheduled H_∞ control of linear parameter-varying systems: a design example. *Automatica*, 31(9), 1251–1261.

Bara, G.I., Daafouz, J., Kratz, F., and Ragot, J. (2001). Parameter-dependent state observer design for affine LPV systems. *International Journal of Control*, 74(16), 1601–1611.

Castillo, F., Witrant, E., Dugard, L., and Talon, V. (2013). Exhaust Manifold Pressure Estimation Diesel Equipped with a VGT Turbocharger. SAE Technical Paper.

Chilali, M. and Gahinet, P. (1996). H_∞ design with pole placement constraints: an LMI approach. *IEEE Transactions on Automatic Control*, 41(3), 358–367.

Fredriksson, J. and Egardt, B. (2002). Estimating exhaust manifold pressure in a turbocharged diesel engine. In *Conference on Control Applications*, volume 2, 701–706.

Heemels, W.P.M.H., Daafouz, J., and Millerioux, G. (2010). Observer-Based Control of Discrete-Time LPV Systems With Uncertain Parameters. *IEEE Transactions on Automatic Control*, 55(9), 2130–2135.

Isermann, R. (2014). *Engine modeling and control: modeling and electronic management of internal combustion engines*. Springer.

Jung, M., Ford, R.G., Glover, K., Collings, N., Christen, U., and Watts, M.J. (2002). Parameterization and Transient Validation of a Variable Geometry Turbocharger for Mean-Value Modeling at Low and Medium Speed-Load Points. SAE Technical Paper.

Mohammadpour, J., Franchek, M., and Grigoriadis, K. (2012). A survey on diagnostic methods for automotive engines. *International Journal of Engine Research*, 13(1), 41–64.

Moulin, P. (2010). *Modélisation et Commande des Systèmes d'Air des Moteurs Suralimentés*. Ph.D. thesis, MINES ParisTech.

Olin, P.M. (2008). A Mean-Value Model for Estimating Exhaust Manifold Pressure in Production Engine Applications. SAE Technical Paper.

Salehi, R., Shahbakhti, M., Alasty, A., and Vossoughi, G.R. (2013). Nonlinear observer design for turbocharger in a SI engine. In *Proceedings of the American Control Conference (ACC)*, 5231–5236.

Yue-Yun Wang and Haskara, I. (2010). Exhaust pressure estimation and its application to variable geometry turbine and wastegate diagnostics. In *Proceedings of the American Control Conference (ACC)*, 658–663.

Zhu, Y. (2002). Estimation of an N–L–N Hammerstein–Wiener model. *Automatica*, 38(9), 1607–1614.