Nonlinear Unknown Input Observer for Intake Leakage Estimation in Diesel Engines

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***Abstract*— Intake leakage estimation problem in diesel engines is addressed in this paper. The need to guarantee high-performance engine behavior and in particular to respect the environmentally-based legislative regulations motivates this work. Today, diesel engines monitoring has become an obligation and a necessity. In this paper, based on a Takagi-Sugeno (TS) fuzzy model of the engine, a nonlinear unknown input observer (NUIO) is used to estimate the intake leakage mass flow rate. The advantage of the proposed method is that no a priori assumption on the intake leakage size is required. The diagnosis system is successfully evaluated using an advanced diesel engine professional simulator AMEsim(LMS).**

***Index Terms*— Diesel engine, Diagnosis, Nonlinear unknown input observers, Takagi-Sugeno models, LMI.**

I. Introduction

On-board diagnosis of automotive engines has become increasingly important because of environmentally based legislative regulations such as OBDII (On-Board Diagnostics-II)[1]. Other reasons for incorporating diagnosis in automotive engines are reparability, availability and vehicle protection. Today, due to the legislations, the majority of the code in modern engine management system is dedicated to diagnosis.

Model-based diagnosis of automotive engines has been considered in earlier papers (see e.g. [2], [3], [4], [5], [6], [7]). However, the engines investigated in these previous works were all gasoline-fuelled and did not include Exhaust Gas Recirculation (EGR) and Variable Nozzle Turbine (VNT). Both these components make the diagnosis problem significantly more difficult since the air flow through the EGR-valve, and also the exhaust side of the engine have to be taken into account. An interesting approach to model-based air-path faults detection for an engine which includes EGR and VNT can be found in [8] and [9]. By using several models in parallel, where each one is sensitive to one kind of fault, predicted outputs are compared and a diagnosis is provided. In particular, the hypothesis test methodology proposed in [8] deals with the multi-fault detection in air-path system. In [9] the authors propose an extended adaptive Kalman filter to find which faulty model best matches with measured data, then a structured hypothesis allows going back to the faults. Recently, a structural analysis for air path of an automotive diesel engine has been developed in order to study the monitorability of the system [10]. Other approaches to detect intake leakages in diesel engines based on adaptive observers are proposed in [11] and [12] and recently in [13]. Note that in all these approaches, the leakage size is assumed to be constant.

In this paper, the considered diesel engine is a four-cylinder engine with a high-pressure exhaust gas recirculation circuit (EGR) and a Variable Geometry Turbocharger (VGT) as described in [14]. The considered fault is an air leakage in the intake manifold and no assumption on its size is needed. A nonlinear mean value model of a diesel engine subject to a leakage in the intake manifold is presented and transformed into a TS fuzzy model [15]. A TS model is a nonlinear model composed of linear models blended together with some nonlinear functions. The interest is to obtain an exact representation of a nonlinear model in a compact set of the state variables. In addition, the structure of TS fuzzy models allows well established tools from control system theory that has been developed over many years. The use of membership functions to describe each nonlinearity and their fuzzy blending through rules to construct the exact representation of the nonlinear model in a compact state space. This systematic method is performed with the aid of the sector nonlinearity approach [16]. In order to estimate the state trajectory a nonlinear unknown input observer (NUIO) proposed in [17] is used. The challenge in the NUIO design is to construct an observer such that it can estimate the states of the considered nonlinear systems asymptotically without any knowledge of the unknown input. The first unknown input observers dedicated to linear systems were proposed in ([18], [19] and [20]). An extension to bilinear and Lipschitz nonlinear systems was the subject of several works in the literature. The reader can refer to [17] and the cited references therein for more information. The proposed approach allows an estimation of the leakage

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mass flow rate. The state and leakage estimations method based on NUNI is evaluated in simulation on a four-cylinder diesel engine model running on AMEsim® platform in co-simulation with Mathworks Matlab®. The AMEsim model used for simulation has been validated on an engine testbed developed by Institut Français de Pétrole (IFP) [14]. The proposed approach provides good estimates of the system states and intake leakage despite the change of operating point.

This paper is organized as follows. The engine apparatus is described in Section II. In Section III a mean value model of diesel engine subject to leakage in intake manifold is given and is transformed into a TS model. Then, a nonlinear unknown input observer for intake leakage estimation is presented in Section IV. The diagnosis system is successfully evaluated using the advanced diesel engine professional simulator AMEsim(LMS) in Section V. Conclusions and future work are finally presented in the last section.

II. Engine description

The diesel engine considered in this paper is a four-cylinder engine with a high-pressure exhaust gas recirculation circuit (EGR) and a Variable Geometry Turbocharger (VGT) as described in [14]. A principle illustration scheme is shown in Fig .1.

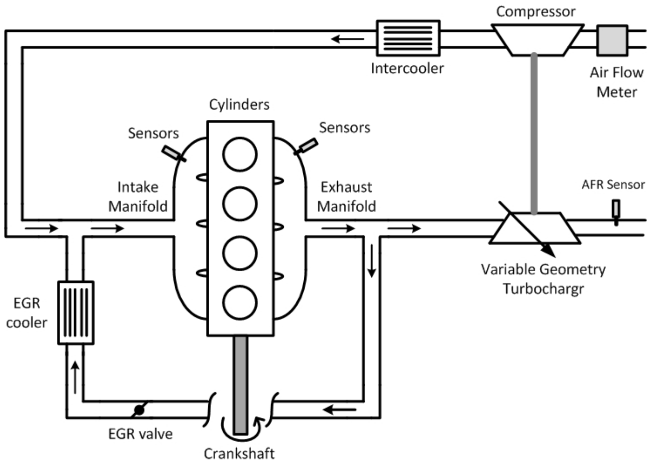

Fig. 1. A schematic picture of air-intake system

The air path system consists of two parts : The turbocharger and Exhaust Gas Recirculation (EGR). The turbocharger is a turbine driven by the exhaust gas and connected via a common shaft to the compressor, which compresses the air in the intake. The exhaust gas recirculation (EGR) allows to recirculate gas from the exhaust manifold to the intake manifold. The recirculation of the exhaust gas through an EGR valve into the intake manifold where it dilutes the incoming fresh air is a well-established and efficient means of reducing in-cylinder NO_x emissions.

III. Intake manifold modelling

Flows from the fresh air (measured by the Manifold Air Flow Meter) and the Exhaust Gas Recirculation (EGR) come into the intake manifold and are aspirated into the cylinders. In numerous references found in the literature [21], mean value engine modelling approaches are considered. It uses temporal and spatial averages of relevant temperatures, pressures and mass flow rates. This leads to a seven-state reference model. The states are the intake and exhaust manifold pressures, the temperature, the composition (the burned gas ratio) and the turbocharger speed. Complexity of the model inspires the control design. Most authors consider a model reduction down to 3 states (see [22] or [23] for example). In the sequel, we propose a reduction down to 2 states. Motivations are given in [24].

We use mass balances, ideal gas law, and consider a low time resolution (180° Top Dead Center time scale). In particular, high frequency aspiration phenomena are not taken into account. A nomenclature is presented in TABLE I (see appendix I).

Total mass balance in the intake manifold Ideal gas law in the intake manifold leads to

$$P_{\mathrm{int}}V_{\mathrm{int}} = M_{\mathrm{int}}RT_{\mathrm{int}} \tag{1}$$

Assuming that variation of temperature is small, the mass balance is written as

$$\dot{P}_{\mathrm{int}} = \frac{RT_{\mathrm{int}}}{V_{\mathrm{int}}}\left(D_{air} + D_{egr} - D_{asp}\right) \tag{2}$$

Typically (see [25] for exemple), we define the aspirated flow as

$$D_{asp} = \eta_{vol}\left(P_{\mathrm{int}}, N_e\right)\frac{P_{\mathrm{int}}}{RT_{\mathrm{int}}}V_{cyl}\frac{N_e}{120} \tag{3}$$

where V_{cyl} is the cylinders' volume. η_{vol} is the volumetric efficiency which is experimentally derived and eventually defined through a look-up table $\eta_{vol}\left(P_{\mathrm{int}}, N_e\right)$.

Composition balance in the intake manifold The burned gas ratio F_{int} is the fraction of burned gas in the intake manifold. It is given by

$$F_{\mathrm{int}} = 1 - \frac{M_{\mathrm{int},air}}{M_{\mathrm{int}}} \tag{4}$$

The composition of the EGR (F_{egr}) is the composition in the exhaust manifold (F_{exh}) delayed by the transport through the EGR pipe. We consider that the delay is negligible, i.e. $F_{egr} = F_{exh}$. The mixing dynamic is modelled as

$$\dot{F}_{\mathrm{int}} = \frac{RT_{\mathrm{int}}}{P_{\mathrm{int}}V_{\mathrm{int}}}\left(D_{egr}\left(F_{exh} - F_{\mathrm{int}}\right) - D_{air}F_{\mathrm{int}}\right) \tag{5}$$

A. Intake manifold subject to leakage modeling

In this subsection, a mean value model of the intake manifold subject to leakage is presented. The leakage is modeled with the assumption that it is located in the intake manifold. However since the temperature and pressure do not change significantly in the region between the compressor and the cylinders, this model is also approximately valid in this larger region. We recall that no assumption about the leakage size is made.

Eq.(2) in the fault-free case model is replaced by

$$\dot{P}_{\text{int}} = \frac{RT_{\text{int}}}{V_{\text{int}}}\left(D_{air} + D_{egr} - D_{asp} - d_{leak}\right) \tag{6}$$

where

$$d_{leak} = A_{leak}\frac{P_{\text{int}}}{\sqrt{RT_{\text{int}}}}\sigma\left(\frac{P_{atm}}{P_{\text{int}}}\right) \tag{7}$$

$$\sigma\left(\frac{P_{atm}}{P_{\text{int}}}\right) = \begin{cases} \frac{1}{\sqrt{2}} & if\, \frac{1}{2}P_{\text{int}} \geq P_{atm} \\ \sqrt{2\frac{P_{atm}}{P_{\text{int}}}\left(1 - \frac{P_{atm}}{P_{\text{int}}}\right)} & if\, \frac{1}{2}P_{\text{int}} \leq P_{atm} \end{cases} \tag{8}$$

d_{leak} represents the leakage mass flow rate from the intake in the presence of a hole.

B. State space representation

Let us set $x_1 = P_{\text{int}}$, $x_2 = F_{\text{int}}$, $u_1 = D_{\text{air}}$, $u_2 = D_{\text{egr}}$ and note : $\alpha_{\text{int}} = \frac{RT_{\text{int}}}{V_{\text{int}}}$ and $\beta_{\text{int}} = \frac{1}{RT_{\text{int}}}V_{cyl}\frac{N_e}{120}$. The state space nonlinear model of the intake manifold subject to leakage is obtained from Eq.(5) and Eq.(6).

$$\begin{aligned} \dot{x}_1 &= -f_1(x_1)x_1 + \alpha_{\text{int}}u_1 + \alpha_{\text{int}}u_2 - \alpha_{\text{int}}d && \text{(9a)} \\ \dot{x}_2 &= -f_2(x_1,u_1,u_2)x_2 + f_3(x_1)u_2 && \text{(9b)} \\ y &= x_1 && \text{(9c)} \end{aligned}$$

with $d = d_{leak}$. The nonlinear functions are given by

$$\begin{aligned} f_1(x_1) &= \alpha_{\text{int}}\beta_{\text{int}}\eta_{vol}(x_1, N_e) \\ f_2(x_1,u_1,u_2) &= \frac{\alpha_{\text{int}}}{x_1}(u_1 + u_2) \\ f_3(x_1) &= \frac{\alpha_{\text{int}}F_{exh}}{x_1} \end{aligned}$$

This representation is one of many possible reformulations of the engine model. It is selected to be used later for the design of an NUIO to estimate the state trajectory. Since $x_1 \neq 0$, the functions f_1, f_2 and f_3 can be assumed to be bounded such that

$$\forall i \in \{1,2,3\}\ ,\ \underline{f_i} \leq f_i \leq \overline{f_i} \tag{10}$$

Because model (9) is nonlinear and the functions f_1, f_2 and f_3 are subject to modeling errors, a linear observer based on a linearization around a given set point would not ensure good performances and robustness in the entire working domain. A way to take into account the nonlinearities of the model is to use a polytopic approach such as the Takagi and Sugeno's modeling [15] .

C. TS's fuzzy modeling

In order to design an NUIO through a fuzzy approach, the nonlinear state model (9) has to be transformed into an equivalent TS fuzzy model [15]. A TS fuzzy model is a nonlinear model composed of linear models blended together with some nonlinear functions. The interest is to obtain an exact representation of a nonlinear model in a compact set of the state variables. The way to derive one TS model from a nonlinear model is to use two nonlinear functions (called membership functions in the TS model) to describe each nonlinearity. This systematic method, called the sector nonlinearity approach [26], results in a TS model with $r = 2^{n_l}$ linear models (rules), where n_l is the number of nonlinearities of the model. In polytopic form we have

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{r}\mu_i(\xi(t))\left(A_i x(t) + B_i u(t) + \Psi_i d(t)\right) && \text{(11a)} \\ y(t) &= Cx(t) && \text{(11b)} \end{aligned}$$

where $x(t) \in \Re^n$ is the state vector, $u(t) \in \Re^m$ is the control input vector, $d(t)$ represents the intake leakage, $y(t) \in \Re^p$ is the output vector and $\xi(t)$ is called the premise vector. A_i, B_i, Ψ_i are matrices with appropriate dimensions. The weighting terms $\mu_i(\xi(t))$ are assumed to be positive scalars and to verify the convex sum property. To obtain these functions, each bounded function f can be easily split using two nonlinear functions $h_1(.) \geq 0$, $h_2(.) \geq 0$ such that $h_1(.) + h_2(.) = 1$ (see, [26]) as follows

$$f(.) = \underline{f}\frac{\overline{f} - f(.)}{\overline{f} - \underline{f}} + \overline{f}\frac{f(.) - \underline{f}}{\overline{f} - \underline{f}} = \underline{f}h_1(.) + \overline{f}h_2(.) \tag{12}$$

This so-called sector nonlinearity approach can be repeated for each nonlinear function of the model. Note that the arguments of the nonlinear functions $\mu_i(.)$ should be measured, otherwise the design of the control synthesis would not be such a trivial task.

Considering the nonlinear model (9), the constant matrices of the considered model (11) are given below

$$\begin{aligned} A_{i=\{1,2\}} &= \begin{bmatrix} -\overline{f_1} & 0 \\ 0 & -\overline{f_2} \end{bmatrix}, A_{i=\{3,4\}} = \begin{bmatrix} -\overline{f_1} & 0 \\ 0 & -\underline{f_2} \end{bmatrix} \\ A_{i=\{5,6\}} &= \begin{bmatrix} -\underline{f_1} & 0 \\ 0 & -\overline{f}_2 \end{bmatrix}, A_{i=\{7,8\}} = \begin{bmatrix} -\underline{f_1} & 0 \\ 0 & -\underline{f_2} \end{bmatrix} \\ B_{i=\{1,2,5,6\}} &= \begin{bmatrix} \alpha_{\text{int}} & \alpha_{\text{int}} \\ 0 & \overline{f_3} \end{bmatrix}, B_{i=\{3,4,7,8\}} = \begin{bmatrix} \alpha_{\text{int}} & \alpha_{\text{int}} \\ 0 & \underline{f_3} \end{bmatrix} \\ \Psi_{i=\{1,\cdots,8\}} &= \begin{bmatrix} -\alpha_{\text{int}} \\ 0 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \end{bmatrix} \end{aligned}$$

IV. FUZZY NONLINEAR UNKNOWN INPUT OBSERVER DESIGN

In this section, inspired by [17] we will present a nonlinear unknown input observer for the TS fuzzy system (11). It is an extended version of the full order unknown input observer design technique presented in

[27]. In [17], the observer based fdesign problem can be divided in : (1) the premise variables do not depend on the unmeasured state variables; and (2) the premise variables depend on the unmeasured state variables. In this work, we are interested only on the first case since the premise variables depend only on the measured state variables.

The considered observer for the system (11) is given as:

$$\dot{z} = \sum_{i=1}^{r} \mu_i(\xi)\left(N_i z(t) + G_i u(t) + L_i y(t)\right) \quad (13a)$$

$$\hat{x}(t) = z(t) - Ey(t) \quad (13b)$$

where $\hat{x}$ is the state estimation vector of x. Matrices N_i, G_i, L_i, $i = 1, \cdots, r$ and E are the observer gains which must be determined such that $\hat{x}$ converges asymptotically to x.

By defining the state estimation error as $e(t) = \hat{x}(t) - x(t)$, the error dynamics can be expressed as

$$\dot{e} = \sum_{i=1}^{r} \mu_i(\xi) N_i e(t) + \sum_{i=1}^{r} \mu_i(\xi)\{N_i + K_i C - (I + EC)A_i\}x + \sum_{i=1}^{r} \mu_i(\xi)\{G_i - (I + EC)B_i\}u - \sum_{i=1}^{r} \mu_i(\xi)(I + EC)D_i d(t) \quad (14)$$

with $K_i = L_i + N_i E$.

Now, if the following matrix equations are satisfied :

$$N_i = (I + EC)A_i - K_i C, \quad \text{with} \quad N_i \quad \text{stable} \quad (15)$$

$$L_i = K_i - N_i E, \quad (16)$$

$$G_i = (I + EC)B_i, \quad (17)$$

$$ECD_i = -D_i, \quad i = 1, 2, \cdots, r, \quad (18)$$

$e(t)$ goes to zero asymptotically and is invariant with respect to the unknown input $d(t)$.

It was proved in [17] that (17) is solvable iff the condition

$$\operatorname{rank}(C(D_1 \cdots D_r)) = \operatorname{rank}((D_1 \cdots D_r)) \quad (19)$$

is satisfied and that the general solution is:

$$E = -D(CD_{T1})^{\dagger} + Y(I - CD_{T1}(CD_{T1})^{\dagger})$$

where Y can be any compatible matrix and $X^{\dagger} = (X^T X)^{-1} X^T$. D_{T1} is a full column rank matrix obtained under condition (19) as follows :

$$(D_1 \quad \cdots \quad D_r)T_D = (D_{T1} \quad 0)$$

where T_D is a nonsingular matrix.

The sufficient conditions under which the observer given by (13) is an NUIO are given in theorem 1.

Theorem 1: [17] The error dynamics given by equation (14) is globally asymptotically stable at the origin if there exits matrices $\bar{K}_i$, $1 < i < r$, $\bar{Y}$, and a positive definite symmetric matrix P such that the following LMIs are satisfied

$$[(I + UC)A_i]^T P + P(I + UC)A_i + (VCA_i)^T \bar{Y}^T + \bar{Y}(VCA_i) - C^T \bar{K}_i^T - \bar{K}_i C < 0, \quad 1<\text{i}<\text{r} \quad (20)$$

where $U = -D(CD_{T1})^{\dagger}$ and $V = I - CD_{T1}(CD_{T1})^{\dagger}$. Solving LMI (20) leads to the determination of matrices P, $\bar{Y}$ and $\bar{K}$. The matrix K_i can be obtained by using $K_i = P^{-1}\bar{K}_i$. The other matrices N_i and L_i can then be deduced easily from equations (14) and (16), respectively.

A. *Unknown input estimation :*

We have shown previously that the estimation error $e(t)$ tends towards zero and is decoupled from the unknown input $d(t)$. So, it is possible to estimate the unknown input from equation (11) by replacing $x(t)$ by its estimate $\hat{x}(t)$. Assuming that the matrix $W = \sum_{i=1}^{r} \mu_i(\xi) D_i$ is of full column rank, then unknown input d can be estimated as follows :

$$\hat{d} = W^{\dagger}(\dot{\hat{x}} - \sum_{i=1}^{r} \mu_i(\xi)(A_i \hat{x}(t) + B_i u(t))). \quad (21)$$

One can see that the structure of $\hat{d}$ depends on the time derivative of $\hat{x}$. Indeed, $\dot{\hat{x}}$ is not available or measured since this depends on $\dot{y}$. One possibility is to use a numerical differentiation method. In this paper, a robust differentiator via sliding mode [28] is applied to estimate the measurement's derivative ($\dot{y}$).

V. MODEL IN THE LOOP : RESULTS

A. *Experiment description and diagnosis setup*

The proposed estimation algorithm, has been tested on a four-cylinder diesel engine model running on AMEsim® platform in co-simulation with Mathworks Matlab®. The AMEsim model used for simulation has been validated on an testbed engine present at IFP [14]. The co-simulation environment (Fig.2.) allows us to run two separate models with two different softwares at the same time. Both solvers compute independently their respective systems and exchange information with a fixed

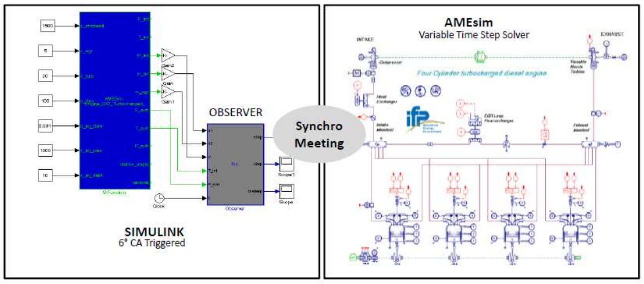

Fig. 2. AMESim/SIMULINK co-simulation platform

communication step interval. The co-simulation platform is used in order to run the engine model on the AMESim side and the control law on the SIMULINK side (At each synchronized meeting time, the engine model sends sensors' data to SIMULINK and the engine control sends back actuators' positions to AMESim).

B. Model validation

The model described above in the section (III-C) was simulated and compared with fresh validation data obtained by AMEsim in [13]. All co-simulation tests have been done on load transients at 1500 *rpm*, i.e, each load kept for 15 seconds. A typical difference between simulated and measured pressures (AMESim) P_{int} was observed and the model was shown to have an average error less than 3% which is acceptable. From the point of view of the authors the sources of error are due to the following :

- In the model heat exchangers volume and pipes volumes are neglected.
- D_{air} is obtained by a Mass Air Flow (MAF) sensor which is positioned (see Fig.1) at the inlet of the compressor. The MAF sensor gives a good measure of D_{air} when the system is stabilized but, during the transient, the measure differs from the flow entering in the intake manifold due to the dynamic into the volume.
- The volumetric efficiency η_{vol} is obtained from a lookup table which differs from real instantaneous value and depends on the engine operating point. This can lead to error on real estimation of the aspirated gas into cylinders.

C. Simulation without leakage : threshold determination

Fig.3 shows the estimation error of P_{int} during a transient load at 3000 rpm i.e, each load kept for 5 seconds. It is clear that the proposed method provides good estimate of the pressure in the intake manifold.

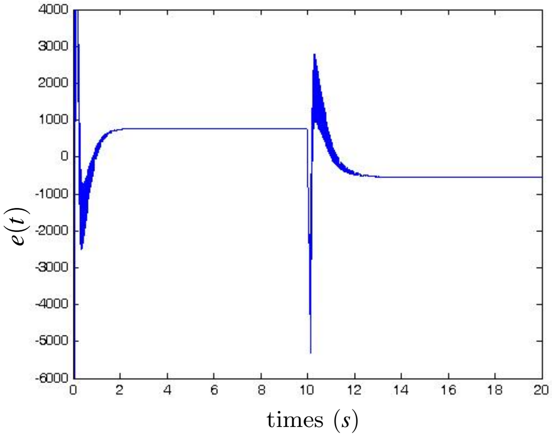

Fig. 3. Estimation error of P_{int} during a transient load at 3000rpm.

The estimation of leakage mass flow rate (d_{leak}) is illustrated in Fig.4. As there is no leakage, the expected estimation is approximately equal to zero all along the simulation.

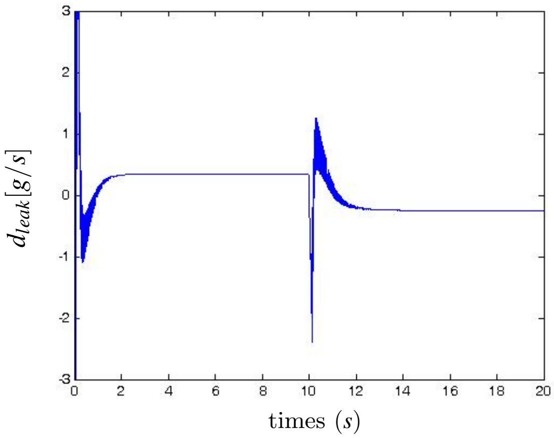

Fig. 4. d_{leak} estimation in a fault-free case

D. Simulation with leakage

In order to assess the effectiveness of the proposed approach, simulations are conducted with leakage in intake manifold with a size of $5mm^2$. The results are presented in Fig.5. The leakage mass flow rate d_{leak} is well estimated all along the simulation despite the change of operating points.

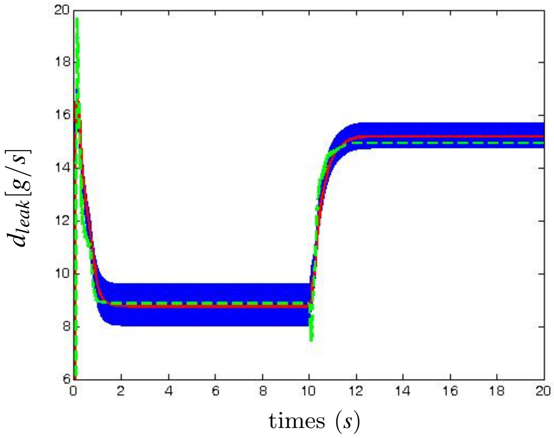

Fig. 5. d_{leak} estimation in a fault case

VI. CONCLUSION

A nonlinear unknown input observer for intake leakage estimation in diesel engines described by Takagi-Sugeno model was considered in this work. Firstly, a mean value model of a diesel engine subject to leakage in the intake manifold was presented and transformed into the equivalent TS fuzzy model. Then, an NUIO for intake leakage estimation was used. The proposed approach allows to estimate jointly the system states and the leakage mass flow rate and no assumption on the intake leakage is needed. The diagnosis system is successfully evaluated using a professional diesel engine simulator AMEsim(LMS).

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APPENDIX I

NOMENCLATURE. I.M. REFERS TO THE INTAKE MANIFOLD

Symb.	Quantity	Unit
P_{atm}	Atmospheric pressure	Pa
P_{int}	Pressure in the i.m	Pa
F_{int}	Fraction of burned gas in the i.m	$-$
T_{int}	Temperature in the i.m	K
F_{exh}	Fraction of burned gas in the e.m.	$-$
D_{air}	Manifold air flow	$Kg.s^{-1}$
D_{egr}	EGR flow	$Kg.s^{-1}$
D_{asp}	Aspirated flow into the cylinders	$Kg.s^{-1}$
D_{leak}	Leakage mass flow rate from the i.m in presence of a hole	$Kg.s^{-1}$
M_{int}	Total mass in in the i.m	Kg
$M_{int,air}$	Air mass in in the i.m	Kg
N_e	Engine speed	rpm
V_{int}	Volume of the i.m	m^3
V_{cyl}	Volume of the cylinders	m^3
A_{leak}	The leakage size	m^2
$A_{leak,max}$	The maximal leakage size	m^2
R	Ideal Gas constant	$J.\left(KgK^{-1}\right)$
η_{vol}	Volumetric efficiency	$-$

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