DIAGNOSIS USING FINITE MEMORY OBSERVERS ON AN UNKNOWN INPUT SYSTEM

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Abstract: In this article, a study of Finite Memory Observers on an unknown input system is treated using augmented states. In this study, noised system is processed and especially state noise due to the modelling of the system with unknown input. After giving a mathematical overview on unknown input observers and after writing Finite Memory Observers principles, results are given according to fault indicators and especially in fault indicator tables.

Keywords: Observers, Finite memory, Unknown input, Residual generation

1. INTRODUCTION

Diagnosis is an important part of vehicle strategies, and especially engine strategies: (Berton, 2004), (Fisher, 2004). In this article, diagnosis take its place in a special part of engine strategy: vehicle pollution control. Actually, a lot of countries all around the world have held conventions to reduce pollutant emissions, references of Kyoto Protocol, (UNFCCC, 2002) can be given to illustrate all these efforts. New developments have been done by vehicle manufacturers to reduce pollutant emissions; the Common Rail system has been designed with all its control strategy.

In a great number of cases, a robust control strategy is enough to assure pollution does not increase up and system works well. But in a few cases, control can be efficient if system information are coherent compared to system state. Two main cases can be considered. In the first case, system modelling is well made, system parameters are well known and will not change in time, so FDI will be done on sensors and actuators. In the second case, it is considered that sensors and actuators are well calibrated and will never have faults, so FDI will be done on model parameters. In the case where control is not efficient, the engine will pollute more and more and over time can be responsible of engine destruction. Then for better work, a supervision strategy should be made to supervise the system and make sure that if faults appear, the system will be able to detect them, locate them and warn the driver to visit a professional garage and also, in the same way, to stop pollution.

A lot of papers treat diagnosis in several ways: Chow-Willsky schemes (Chow, 1984), parity relations (Cocquempot, 2000), fault detection using observers (Kratz, 2003), can be cited for model-based methods; and in another way Principal Component Analysis (PCA) (Gertler, 1999), and statistic methods (Basseville, 1998).

In this article, a model structure is known so model-based diagnosis methods can be applied, and especially observers can be implemented to compare measurements and estimated measurements. In this case, Finite Memory Observers method is used.

A first study on diagnosis of diesel injection system has been done (Graton, 2004), this study can be considered as a feasibility study. In fact, the Resistant Torque in the previous paper was supposed known, that is not a real configuration because no measurement, and no available estimation on Resistant Torque can be given to the system.

So, the Resistant Torque in this case must be taken as an unknown input of the system. This new study gives some results in this way, we take the Resistant Torque as an unknown input on the Common Rail system. Several references can be given to illustrate this approach: (Nikoukhah, 1994), (Gleason, 1990) and (Hou, 1992).

2. DIESEL INJECTION SYSTEM OVERVIEW

The aim of this section is to make a fault detection on a system which has an unknown input. First of all, system model description will be given as a physical structure with differential equations. In (Graton, 2004), Resistant Torque is supposed known and constant. In this model, in equation (2), Resistant Torque described by T_R can not be measured, and can not be estimated and it's not possible, in whatever manner so ever, to get an idea of what it could be. In this section, a solution will consist in defining the Resistant Torque as an augmented state.

2.1 Continuous states: Differential Equation Representation

The system representation in (Graton, 2004) is given by those three differential equations:

$$\dot{P}_{rail}(t) = KQ_p(t) - Q_i(t) - Q_d(t) - Q_l(t) \quad (1)$$

$$\dot{\omega}_{eng}(t) = c_7F(t) - c_8T_R(t) - c_9\omega_{eng}(t) \quad (2)$$

$$\dot{S}_{IMV}(t) = c_{10}I_{IMV}(t) - c_{11}S_{IMV}(t) + c_{12} \quad (3)$$

where in (1), K is a constant, P_{rail} represents the Rail pressure [Pa], Q_p the Pump flow [m^3/s], Q_i the Injection flow [m^3/s], Q_d the Discharge flow [m^3/s] and Q_l the Leakage flow [m^3/s]; in (2), ω_{eng} represents the Engine speed [rpm], F the mass of fuel injected [mg/stroke] and T_R the Resistant Torque [N.m]; in (3), S_{IMV} represents the Inlet Metering Valve (IMV) Section [m^2] and I_{IMV} the IMV current [A].

In the case of use, Resistant Torque T_R includes a lot of different torques and particularly the road resistant torque that can not be measured or estimated. It's obvious that Resistant Torque can not be constant, it is obliged to change/vary in time especially in rises and descents. To consider Resistant Torque variations in the system model, one solution proposed is to augment the model with one state corresponding to Resistant Torque. This added state introduces the following dynamics equation to previous equations (1, 2, 3) written as follows:

$$\dot{T}_R(t) = 0 \quad (4)$$

Resistant Torque is considered now as an additional state which has zero dynamic. State noises and especially Resistant Torque noise will give a uncertainty to the Resistant Torque; that one can vary. It will be explained more in detail in a further section.

The system equation can now be written like this:

$$\begin{aligned}
\dot{P}_{rail}(t) &= \left(c_1\omega_{eng}(t)^2 + c_2\omega_{eng}(t)\right. && (5)\\
&\quad \left.+c_3\right) S_{IMV}(t) - c_4\omega_{eng}(t)F(t)\\
&\quad -c_5P_{rail}(t)^{1.88} - c_6\sqrt{P_{rail}(t)}Disch(t)\\
\dot{\omega}_{eng}(t) &= c_7F(t) - c_8T_R(t) - c_9\omega_{eng}(t) && (6)\\
\dot{S}_{IMV}(t) &= c_{10}I_{IMV}(t) - c_{11}S_{IMV}(t) + c_{12} && (7)\\
\dot{T}_R(t) &= 0 && (8)
\end{aligned}$$

2.2 Discrete states

Let the state vector be:

$$X(k) = \begin{pmatrix} P_{rail}(k) \\ \omega_{eng}(k) \\ S_{IMV}(k) \\ T_R(k) \end{pmatrix}$$

where P_{rail}, ω_{eng}, S_{IMV} and T_R are described in the previous subsection but they are all normalized in percent [%] to avoid numerical problems. Let the input vector be:

$$u(k) = \begin{pmatrix} I_{IMV}(k) \\ F(k) \\ Disch(k) \end{pmatrix}$$

where I_{IMV}, F and $Disch$ are described in the previous subsection. Command signals are measured.

The system so defined is:

$$\begin{aligned}X_1(k+1) &= X_1(k) + T_e\left[\left(c_1 X_2(k)^2 + c_2 X_2(k) + c_3\right) X_3(k) - c_4 X_2(k) u_2(k) \right.\\ &\quad \left. - c_5 X_1(k)^{1.88} - c_6 \sqrt{X_1(k)} u_3(k)\right]\\ X_2(k+1) &= X_2(k) + T_e\left[c_7 u_2(k) - c_8 X_4(k) - c_9 X_2(k)\right]\\ X_3(k+1) &= X_3(k) + T_e\left[c_{10} u_1(k) - c_{11} X_3(k) + c_{12}\right]\\ X_4(k+1) &= X_4(k)\end{aligned}$$

where T_e is the sample time and c_i constant parameters.

It has been seen in the previous section that the unknown input is taken as an additional state which has a zero-dynamic. Unknown input variations do not exist in such a case. This augmented state can not be better modelled because of the lack of information in it. To give it some possible unknown variations, a standard deviation is added in the additional state equation. This standard deviation is modelled by random noise $\beta(k)$; $\beta(k)$ is a zero-mean white Gaussian noise with a σ standard deviation. Some simulation tests have been done on the characterization of σ-parameter. Tests with σ near unity seems a good choice in simulation cases. A new characterization will be done on the Common Rail System. That gives dispersion values of additional state variation:

$$X_4(k+1) = X_4(k) + \beta(k) \tag{9}$$

The augmented state equation model can be written in a stochastic case:

$$X(k+1) = A_a(\rho(k))X(k) + B_a(\rho(k))u(k) + f_a(k) + w_a(k) \tag{10}$$

$$y(k) = C_a X(k) + v(k) \tag{11}$$

where A_a is the augmented state matrix, B_a the input-state matrix, C_a the measurement matrix, f_a constant component due to linear interpolation, w_a and v state and measurement noises.

State noise and measurement noise are supposed zero-mean white Gaussian and mutually uncorrelated, they are uncorrelated with initial state $x(0)$. Covariance matrix of state noise and measurement noise are defined by W and V matrixes respectively.

2.3 Output equation

As said previously, Resistant Torque can not be in the measurement equation because it is unmeasurable. The system has no sensor on IMV Section; only Rail Pressure and Engine Speed are measured. In this study, the output equation is given as:

$$y(k) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} X(k) \tag{12}$$

where $y(k)$ is a measurement vector.

3. FINITE MEMORY OBSERVERS

3.1 Definition of the state estimation

Let us start with the system mathematical representation given by (10). The delayed state relation $X(k-i)$ can be expressed in terms of the current state $X(k)$ with the following statement:

$$\begin{aligned}X(k-i) &= \prod_{j=i}^{1} A_a^{-1}(k-j) X(k)\\ &\quad - \sum_{j=1}^{i} \left(\prod_{j=i}^{1} A_a^{-1}(k-l)\right)\\ &\quad [B_a(k-j)u(k-j) + f_a(k-j)]\end{aligned}$$

The output equation becomes :

$$\begin{aligned}y(k-i) &= C \prod_{j=i}^{1} A_a^{-1}(k-j) X(k)\\ &\quad - C \sum_{j=1}^{i} \left(\prod_{j=i}^{1} A_a^{-1}(k-l)\right)\\ &\quad [B_a(k-j)u(k-j) + f_a(k-j)]\end{aligned} \tag{13}$$

Given: $Y(k-L) = \left[y(k-1)^T \dots y(k-L)^T\right]^T$, $U(k-L)$ and $Y(k-L)$ are build in the same way; then the system equation is:

$$Y(k-L) = M_L(k)X(k) - H_L(k)U(k-L) - N_L(k)F(k-L).$$

Isolating the current state variable from the above equation, gives :

$$M_L(k)X(k) = Y(k-L) + H_L(k)U(k-L) + N_L(k)F(k-L)$$

This equation can be solved by the least square method, giving :

$$\begin{aligned}\hat{X}_L(k) &= [M_L^T(k) R_L^{-1}(k) M_L(k)]^{-1} M_L^T(k) R_L^{-1}\\ &\quad [Y(k-L) + H_L(k)U(k-L)\\ &\quad + N_L(k)F(k-L)]\end{aligned} \tag{14}$$

Remark 1. The Finite Memory Observers method is a deadbeat observer. The convergence of $\hat{x}_L(k)$ will be released in L steps, where L is the window length of the Finite Memory Observer.

3.2 Residual generation

Residual generation takes a great part in Fault Detection and Isolation (FDI), it is important in diagnosis. In (Graton, 2004), Residual Generation is made by comparison between the two estimations of $x(k)$ denoted $x_{L_1}(k)$ and $x_{L_2}(k)$ respectively, that gives:

$$r_1(k) = x_{L_2}(k) - x_{L_1}(k)$$

In a fault free case, this residual is close to zero. Another Residual Generation can be done easily by comparison between measurement and an estimated measurement

$$r_2(k) = y(k) - Cx_{L_1}(k)$$

Up to now, estimations by Finite Memory Observers are given thanks to all measurements. Other observer subsystems can be built with a new instrumentation configuration. It can be considered that estimations can be made thanks to only several measurements. The necessary condition, to make this observer work, is given by the system observability. In the physical approach on Diesel Injection System, only the case with Rail Pressure measurement on the observer input has the observability condition. The case with only Engine Speed measurement in the observer input is not observable. All these Residual Generations are called Observer Bank. They are drawn and explained on the following figure.

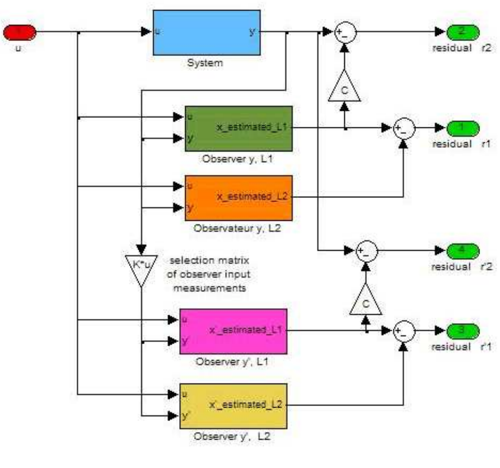

Fig. 1. Schema of an Observer Bank

4. APPLICATION ON DIESEL INJECTION SYSTEMS

In this section, the first part is dedicated to comparing the observer to the physical model. In the second part, residuals are computed and analyzed.

4.1 Observer convergency

In a first step, observer convergency is tested in the Fuel Injection Equipment (FIE) model presented in section 2 with Resistant Torque as an unknown input. According to Figure 2, it's obvious that the observer converges to physical values. Focusing on Resistant Torque estimations, the β variance choice gives different estimations. After choosing a good variance to β, the Resistant Torque is well estimated; noises are minimized. It is a mean convergency to model values except for two periods corresponding to an abrupt deceleration at time instant $t = 20s$ and an abrupt acceleration at time instant $t = 40s$. At these two time instants, greater peaks can be seen.

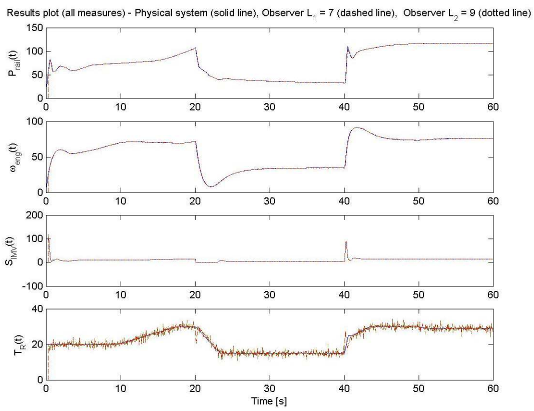

Fig. 2. Observer efficiency in FIE model

4.2 Diagnosis results

In a second step, residual generation is studied in two different observer configurations; the first one with all measurements and the second one with only rail pressure measurement in observer inputs. In Figure 3.a, residuals 2 and 4 (corresponding to comparison between two estimations on engine speed and resistant torque) are noisy and close to zero. All other residuals are closed to zero except at time instants $t = 20s$ and $t = 40s$. In Figure 3.b, all residuals are close to zero except at time instants $t = 20s$ and $t = 40s$. The raison that residuals are not close to zero at these two time instants is due to a bad system design. Three different solutions are offered to avoid this bad detection. The first one consists of switching in a blind strategy during abrupt accelerations and decelerations, but information will be lost. It is not a professional solution. The second solution is to put a greater state noise variance, but this strategy gives worse estimations. The last solution is to play with fault indicators as it is seen after.

Except during abrupt accelerations and decelerations, when there is no fault on the system, residuals are close to zero. When a fault occurs,

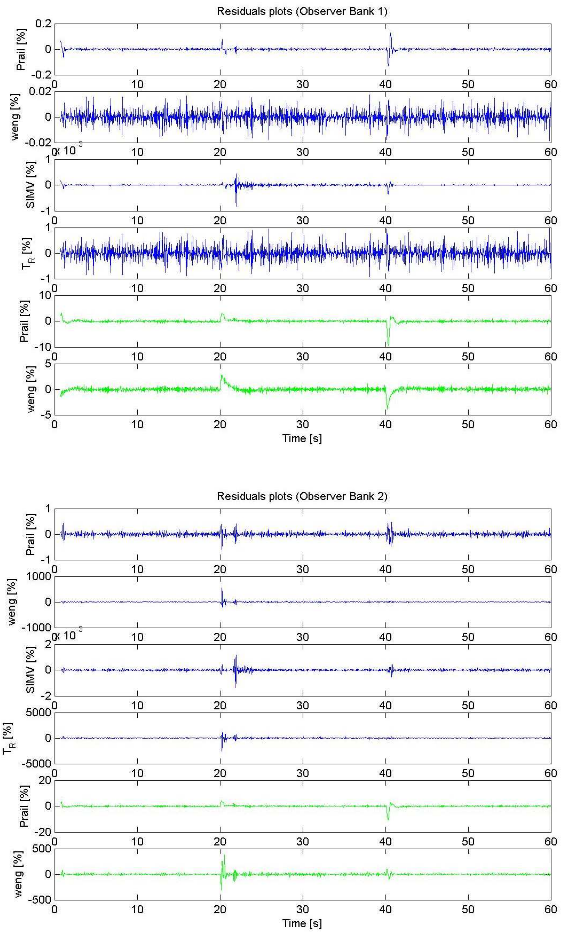

Fig. 3. Residuals in a free fault case (a) all measurements (b) only rail pressure measurement in observer inputs

a fault signal can be recognized, at time instant $t = 50s$ and $t = 55s$ on Figures 4.2 and 4. Here the sensibility to a rail pressure fault can be observed on each residual, so a fault indicator can be built. 0:s describes the residual is not sensitive to fault, 1:s when it is, and X:s when it is but slightly. A fault indicator table can be drawn up with corresponding 0:s, 1:s and X:s.

Table 1. Residuals structure by FMO on a Rail Pressure sensor fault

		Rail Pressure Fault	
		Obs. 1	Obs. 2
	Rail pressure	1	1
Residual	Engine speed	0	X
r_1	IMV Section	X	1
	Resistant Torque	0	X
Residual	Rail Pressure	1	1
r_2	Engine speed	0	1

Fault detection table can be done when a Engine speed sensor fault or when an IMV Current or a Fuelling actuator fault occur. Each fault gives different fault detection tables. All these fault detection can be summarized in the table below.

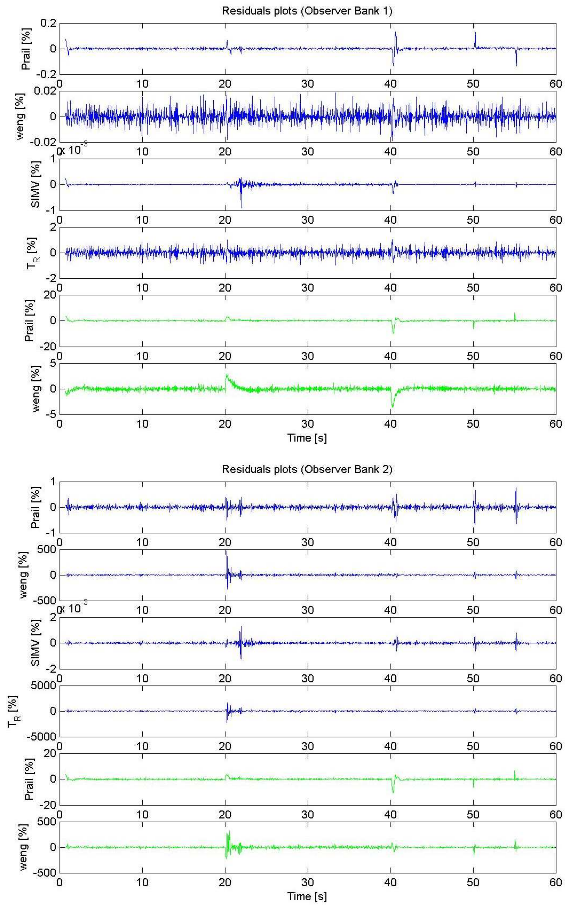

Fig. 4. Residuals in a Rail pressure sensor fault case (a) all measurements (b) only rail pressure measurement in observer inputs

4.3 Fault Isolation

The last step in this section is to do fault isolation. The table 2 shows that an Engine speed sensor fault is easily isolable compared to other indicators. But it is harder to isolate a Rail pressure sensor fault to a IMV Current actuator fault. The two fault indicators are similar. X:s in fault indicators can have a fault signification or a no-fault signification; it depends on the threshold choice, on fault amplitude and on noise amplitude. So some configurations can give the same fault indicator. A Fuelling actuator fault is totally non detectable and non isolable.

From a second point of view, a hard acceleration or deceleration indicator is easily isolable to fault indicators; particularly thanks to residual r_2. This residual is {1;1} only during strong accelerations and decelerations. The problem discovered in the previous section with strong accelerations and decelerations is solved now thanks to fault indicators.

5. CONCLUSION

The Fault Detection and Isolation (FDI) problem for FIE is treated in this paper. A realest

Table 2. Residuals structure by FMO on sensor and actuator fault

		Fault on sensor		Fault on actuator			
		Rail Pressure	Engine Speed	IMV Current	Fuelling	Accel.	Decel.
	Rail pressure	1	0	1	0	1	1
Residual	Engine speed	0	1	0	0	0	0
r_1	IMV Section	X	0	X	0	1	1
	Resistant Torque	0	1	0	0	0	0
Residual	Rail Pressure	1	0	1	0	1	1
r_2	Engine speed	0	1	0	0	1	1
	Rail pressure	1	0	1	0	1	1
Residual	Engine speed	X	0	0	0	1	0
r'_1	IMV Section	1	0	X	0	1	1
	Resistant Torque	X	0	0	0	1	0
Residual	Rail Pressure	1	0	1	0	1	1
r'_2	Engine speed	1	0	1	0	1	1

system modelling was done to allow Resistant Torque variations. A solution is to make Resistant Torque a augmented state. This augmented state was taken with a zero mean dynamic. Actually, Resistant Torque dynamic is a zero-mean white Gaussian random noise. After a short study of Finite Memory Observers, results are given accompanied by residual indicator table. This paper gives mitigated results. In fact, in a first step, a good detectability is done on each fault except a Fuelling actuator fault. In a second step, Engine speed fault isolation is relatively easy; strong accelerations and decelerations are easily isolable to real faults. On the other head, Rail pressure fault and IMV current faults are hardly isolable.

Observer bank gives more fault indicators, and makes an easiest FDI even if two fault indicator can be roughly the same.

In this paper, model limits are encountered. Resistant torque problem is solved but this implies some FDI problems. Furthermore, problems like the discharge can be solved if a new control is given without boolean actuator; a new process strategy is developed in FIE. Further study will involve the injection system synchronizing to Engine speed to remove Resistant torque problems.

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REFERENCES

Basseville, M. (1998). On-board component fault detection and isolation using the statistical local approach. *Automatica* **34(11)**, 1391–1415.

Berton, A. and Nyberg M. and Frisk E. (2004). Improving diagnosis performance on atruck engine making use of statistical charts. In: *IFAC Advances on Automotive Control (AAC'04)*.

Chow, E.Y. and Willsky A.S. (1984). Analytical redundancy and the design of robust detection systems. *IEEE Transactions On Automatic Control* **29(7)**, 603–614.

Cocquempot, V. and Christophe C. (2000). On the equivalence between observer-based and parity space approaches for fdi in non-linear systems. In: *IFAC Safeprocess Symposium, Budapest, Hungary*. pp. 232–237.

Fisher, D. and Schöner H.-P. and Isermann R. (2004). Model-based fault detection for an active vehicle suspension. In: *IFAC Advances on Automotive Control (AAC'04)*.

Gertler, J. and Li W. and Huang Y. and McAvoy T.J. (1999). Isolation enhanced principal component analysis. *AIChe Journal* **45**, 323–332.

Gleason, D. and A. Andrisani (1990). Observer design for discrete systems with unknown exogenous inputs. *IEEE Transaction on Automatic Control* **35(8)**, 932–935.

Graton, G. and Fantini J. and Kratz F. and Ragot J. and Dupraz P. (2004). Diagnosis of diesel injection system using finite memory observers. In: *IFAC Symposium on Advances in Automotive Control*. pp. 398–403.

Hou, M. and Muller P.C. (1992). Design of observers for linear systems with unknown inputs. *IEEE Transaction on Automatic Control* **37(6)**, 871–875.

Kratz, F. and Aubry D. (2003). Finite memory observer for state estimation of hybrid system. In: *IFAC American Control Conference (ACC 2003)*.

Nikoukhah, R. (1994). Innovations generation in the presence of unknown inputs: application to robust failure detection. *Automatica* **30(12)**, 1851–1867.

UNFCCC (2002). The United Nations Framework Convention on Climate Change.