A Linear Approach with μ-Analysis Control Adaptation for a Complete-Model Diesel-Engine Diagnosis

Chady Nohra[1], Hassan Noura[2], Rafic Younes[3]

1,2.Laboratoire des Sciences de l'Information et des Systèmes (LSIS),Paul Cézanne University, Aix Marseille III, 13397 Marseille Cedex 20, France

1cnohra@ndu.edu.lb

2hassan.noura@lsis.org

3. Mechanical Engineering Department,Lebanese University,Rafic Hariri Campus, Lebanon

ryounes@ul.edu.lb

Abstract: This paper proposes an innovative fault-diagnosis system for a turbocharged diesel engine with variable-geometry turbocharger control. Numerous and diversified actuator faults are identified and analyzed such as air-leakage in the admission collector, compressor malfunctioning, intake-valves fault, intercooler fault, deterioration in the turbine-compressor coupling, defect in the variable geometry of the turbine. Furthermore, a complete non-linear engine model with four state variables is adopted. The proposed strategy consists in developing Fault Detection and Estimation algorithm (FDE) based on the theory of μ analysis control, operated on a linearization LTI model of the diesel, permits a fault detection and estimation while attenuating the effect of uncertainties, disturbances and noise. Simulations with LTI Diesel model in the presence of noise and uncertainties were carried out which demonstrated the effectiveness of the proposed algorithm. Moreover, the robustness properties of the used H-infinity/μ FDE filters exhibited significant rejection of disturbances and noise-effects attenuation as well as robustness against uncertainties which make the proposed strategy adequately close to the conditions of the real physical system.

KeyWords: Diagnosis, Fault detection and estimation (FDE); Diesel engine; H∞/ μ control; structured singular value.

1 INTRODUCTION

Most previous researches in the field of diesel-engine diagnosis were conducted for a reduced number of parts of the diesel engine and did not consider a complete engine model. Furthermore, some of these methods have been based on statistical and experimental studies. Among these studies: the combustion diagnosis using neural networks [13], vibratory signals using Wavelet theory [17], fuel injection faults using fuzzy logic [18] and wavelet-theory based "ring gumming fault" [19]. Other studies involved model-based diagnosis for some specific parts in the Diesel engine such as faults in the cooling system of the diesel engine [16], fault of the combustion process [12], and air-circuit faults [20] [15].

Turbocharger faults were studied in [11] by using neural networks. Cylinder-faults studies could be found in [14].

The strategy proposed in this paper aims at detecting, estimating six actuators faults in different parts of the diesel engine equipped with a variable-geometry turbocharger. Additionally, a complete model of the Diesel engine is adopted and an FDE system based on the “μ analysis” Control theory is developed. The developed observer is composed out of a model estimator and a controller; the controller provides the estimator with the parameter faults and aims at zeroing the error-difference between the estimated state variables and the real ones. The μ analysis Control theory and the linearized model were adopted to synthesize an efficient and innovative controller for this type of applications. Once the controller is achieved, the linear system is replaced by the nonlinear one, in order to eliminate the linearization error and to extend the observation area.

The paper is divided into 6 major parts. Part 2 shows the diesel engine model. Some comprehensive engine faults and their appearances in the system state-variables model are exploited in section 3. Section 4 describes in general the control based observer. Section 5 discusses in detail the proposed strategy wherein the FDE algorithm based on the μ-synthesis method is developed and implemented. Section 6 exhibits the simulations that were carried out to validate our approach and which show effectiveness in the process of fault detection on the diesel engine. Finally, we wrap up with a conclusion.

2 DIESEL ENGINE MODEL

The Diesel Engine can be described by the following nonlinear system of equations and the block diagram of Fig. 1.

$$\begin{cases} \dfrac{dx}{dt} = \xi(x,u,t) \\ y = x \end{cases} \tag{1}$$

x : state vector, u : input vector, t : time, ξ is a non linear function, y is the output vector which is, in this case, the state variables vector.

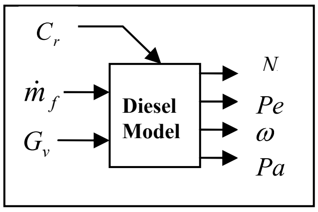

Figure 1. Diesel Engine Block Diagram

Vector x regroups engine rotational speed w,turbocharger rotational speed w_{tc}, and admission and exhaust pressure p_a and p_e, respectively. Vector u contains fuel-oil mass flow rate $\dot{m}_f$, resistance load C_r and variable geometry turbocharger.

The model used in this paper is the one developed by Xavier Doveefaz [23]. It can be expanded in the following way:

$$
\begin{aligned}
& I_{tc} w_{tc} \frac{dw_{tc}}{dt} = [\eta_m P_t(p_e, w_{tc}, GV) - P_c(p_a, w_{tc})] \\
& J \cdot w \cdot \frac{dw}{dt} = \left[\eta_e(p_a, w, m_f) \cdot \dot{m}_f \cdot P_{ci} - pmf(w) \cdot \frac{Cy}{4\pi} \cdot w - C_r \cdot w\right] \\
& V_e \frac{dp_e}{dt} = r.T_e(p_a, w).[m_a(p_e, w_{tc}) + m_f - \dot{m}_t(p_a, w_{tc})] \\
& V_a \frac{dp_a}{dt} = r.T_a(p_a, w).[\dot{m}_c(p_a, w_{tc}) - \dot{m}_a(p_a, w)]
\end{aligned}
\tag{2}
$$

Pt , Pc , pmf , mc , me , mt , ma are the power of the turbine, power of the compressor, the average friction pressure in the engine, air flow rate in the compressor, exhaust, the turbine and the admission chamber respectively. I_{tc}, J : are the turbo compressor and the motor inertia respectively (J is supposed constant and independent from the angular position θ).

V_e, V_a : are respectively the admission and exhaust chamber volume.

p_a, p_e, w, w_{tc} : are the state variables which represent respectively the admission pressure, exhaust pressure, rotational speed, and turbo compressor rotational speed. T_e, T_a : are exhaust and admission chamber temperature respectively.

η_e, η_m : are respectively the mechanical and effective efficiency.

C_y : Motor Cylinder.

r : is the perfect gas constant.

These are semi-empiric nonlinear functions issued from experience [23].

Output is given by:

$$y = [N_{tc}, pe, \omega, pa] \tag{3}$$

Refer to Engine Specifications [23] for the Engine Characteristics and the notifications used for the foregoing parameters of the model.

3 FAULTS AND MODELING

In order for the study to be more comprehensive and reflect as many frequent fault occurrences as possible, the following common faults will be considered in this paper:

Fault n°1: air leakage in the intake chamber

This fault reflects any leakage in the admission chamber. Air leakage is modeled by the diameter of a hole in the intake chamber. As the leakage flow-rate varies according to the pressure, it can be modeled using the relation of Saint-Venant:

$$m_{leakage} = C_C\left(\pi \times \frac{d}{2}\right)^2 \frac{Pa}{\sqrt{r \times Ta}} \sqrt{\frac{2Cp}{r}} \sqrt{1 - \left(\frac{P_{atm}}{Pa}\right)^{(\gamma-1)/\gamma}} \tag{4}$$

Where d represents the diameter of the supposed hole, and C_C represents the out-flow contraction factor.

Fault n°2: malfunctioning of the compressor

This fault reflects a reduction in the compressor air flow rate due for example to damage in the compressor, or from an air filter problem; this fault can be modeled by multiplying the compressor flow rate by a constant which is less than 1:

$$\dot{m}_c = (1 - K_c)\dot{m}_c \tag{5}$$

Fault n°3: fault in opening the intake valves

It characterizes a bad opening of the admission valves; intake flow rate inhaled by the cylinders will be reduced:

$$\dot{m}_a = (1 - K_a)\dot{m}_a \tag{6}$$

Fault n°4: fault in the intercooler

It represents a bad exchange of temperature; therefore the intercooler efficiency $\eta_{\text{intercooler}}$ will be reduced:

$$\eta_{\text{intercooler}} = (1 - K_{\text{intercooler}})\eta_{\text{intercooler}} \tag{7}$$

Fault n°5: fault in the turbocharger coupling

This fault type exhibits a coupling deterioration between the turbine and the compressor, therefore the coupling mechanical efficiency η_m will be reduced and this is modeled the same way as for the previous fault:

$$\eta_m = (1 - K_{t-c})\eta_m \tag{8}$$

Fault n°6: fault in the geometry of the turbine

This is a fault in the turbocharger variable geometry; the geometry control coefficient GV will be reduced .In this case the observed Gv is different then the target Gv :

$$GV = (1 - K_{Gv})GV \tag{9}$$

4 CONTROL BASED OBSERVER

Consider the following system which represents the diesel engine linearization at a functioning point:

$$
\begin{aligned}
& \dot{x} = A.x + B.u + a + B_a k_a \\
& y = C.x + D.u + c
\end{aligned}
\tag{10}
$$

Where A,B,C,D are the matrices of the linear LTI system. x, u, y are the state vector, control vector, and output vector, respectively; k_a the actuator fault-parameter vector; a and c are constants depending on the equilibrium point.

Now consider the following estimator structure:

$$\dot{\hat{x}} = A.x + B.u + a + U_x$$
$$\hat{y} = C.\hat{x} + D.u + c \qquad (11)$$

U_x represent the control vector that make estimator (11) tracking the system (10) by zeroing the error between these two systems. The errors between the real state variables and the estimated ones verify the following equations:

$$\dot{e} = Ae - U_x + B_a K_a$$
$$e_y = Ce \qquad (12)$$

Finally, after some manipulations, the previous system will have the following form ready for control-algorithm implementation:

$$\dot{e} = A.e + B_1 w + B_2 U$$
$$e = C_1.e + D_{11} w + D_{12} U \qquad (13)$$
$$e_y = C_2 e + D_{21} w + D_{22} U$$

$w = k_a, U = U_x, B_1 = B_a, B_2 = -I, C_1 = I, C_2 = C,$
$D_{11} = D_{12} = D_{21} = D_{22} = 0$

Where I is the identity matrix.The control vector U is calculated to make the error vector e approaches zero independently from the w perturbations-vector and this by minimizing the H∝ norm of the transfer function between perturbations-vector (which is in this case an unknown vector) and output vector. It is noticed that if the error-vector approaches zero such that $\|A.e\|_\infty$ and $\|C_2.e\|_\infty$ has a magnitude relatively small comparing to $\|B_a K_a\|_\infty$, then $B_2.U$ approaches $B_1.\omega$.

Thus, the value of the parameter fault vector can be computed as follows:

$$K_a = (B_a^T.B_a)^{-1}(B_a^T.B_2.U) \qquad (14)$$

5 μ- OBSERVER DESIGN

The nonlinear plant could be linearized at an equilibrium point in order to create a nominal plant Go (Fig-2) and form the diesel error system (13). The aim of the robust control under model mismatch is the disturbance rejection, the tracking of a predefined reference (in our case equal zero). The robust controller is realized by μ synthesis.

Linear H∞, respectively μ control syntheses are promising methods on the palette of the robust control systems. These postmodern techniques date back to around two decades [20]. Progressively it gains ground by the more and more powerful computational soft- and hardware, [21], [22]. One of the biggest advantages of these methodologies (beyond the well defined mathematical backgrounds) might be the robustness itself. Robustness against model mismatches, against disturbances.

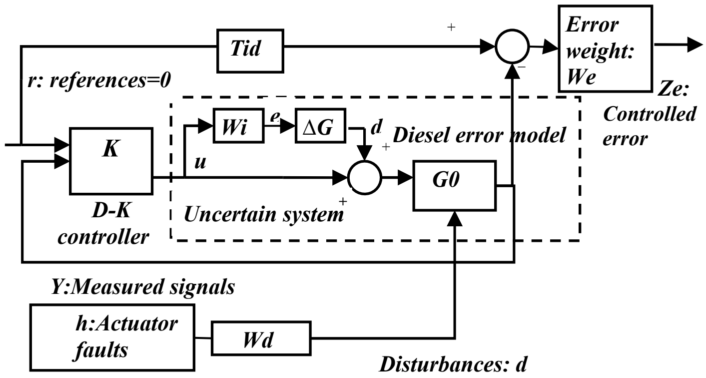

Figure 2. Augmented System

For robust control synthesis, consider the augmented system drawn in the Figure-2.Consider the closed-loop system which includes the feedback structure of the model G0 and controller *K*, and elements associated with the uncertainty models and performance objectives. In the diagram, *r* is the reference, *u* is the control input, *y* is the output, *n* is the measurement noise, and Ze is the deviation of the output from the required one.

Model based control systems use the mathematical abstraction of the actual plant to be controlled. However, vast identification techniques can be found in the literature, perfect fitting of the model-real plant does not exist. Therefore, the model (or nominal plant) always contains neglected dynamics of the real world. In our case, the input multiplicative uncertainty ΔG is used, because it specifies the digression, the frequency depending difference (in percentage) between the nominal and the actual plant.

The weighting function We chosen for tracking errors can be thought as penalty function. We should be large in frequency range where small errors are desired and small where larger errors can be tolerated. To achieve perfect tracking (i.e. integral action) We weights should be large at very low frequency to imitate integrator. At the same time, good tracking property and nominal model validity can be treated as a trade-off. Uncertain model cannot be forced to assure nominal performance requirements. *Tid* is the model matching function which generally is an ideal transfer function of the plant. .
The main performance objective is that the transfer function from *r* to *Ze* be small, in the $\|\cdot\|_\infty$ sense, for all possible uncertainty transfer functions Δ_m .

The weighting function *Wn* represents impact of the different frequency domains in terms of the sensor noise. Weighted sensor noises *Wn* and external disturbances *Wd* are input weights. Therefore, their selection is slightly different from the definition of output scales. The role of weights for these signals is basically the opposite of the role of weights for output weights discussed so far. Inputs to the weights are signals whose frequency responses are flat and unit size. The weights themselves contain scale factors and frequency shaping that match the size, units and frequency content of the true inputs. Input weights can be either frequency dependent or constant. Necessary and sufficient conditions for robust stability and robust performance can be formulated in terms of the structured singular value denoted as μ, DOYLE, (1982)[1]. Now, the design setup should be formalized as a standard design problem as illustrated in Figure-3. The augmented Δ-P-K structure can be created by applying the weighting functions given above and the inputs can be written as:

$$\tilde{w} = \begin{bmatrix} r & n & h \end{bmatrix}^T,\ \tilde{z} = \begin{bmatrix} z_e & u \end{bmatrix}^T \qquad (15)$$

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix};$$

By introducing the lower LFT of the (*P, K*) pair, i.e.

$$M = F_l(P,K) = P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21} \qquad (16)$$

One gets back the $\Delta - M$ structure (Figure-3.1). The robustness and performance analysis of the augmented plant can be fulfilled by the partition blocks of the *M*:

$$\begin{bmatrix} e \\ \tilde{z} \end{bmatrix} = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} d \\ \tilde{w} \end{bmatrix}$$

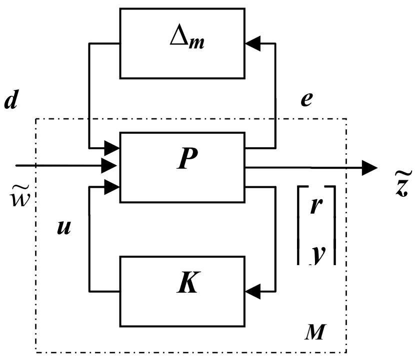

Figure 3. Generalized Δ-P-K structure

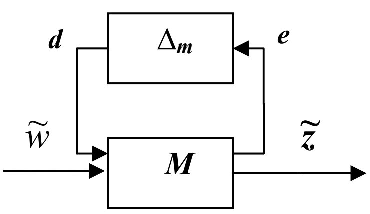

Figure 3.1 Generalized Δ-M structure

Our goal is to guarantee the robust performance of the closed-loop system in the face of nominal plant perturbation. Robust performance is equivalent to

$$\left\| F_u(M,\Delta) \right\| < 1$$

Where $F_u(M,\Delta)$ is the upper linear fractional transformation:

$$F_u(M,\Delta) = M_{22} + M_{21}\Delta(I - M_{11}\Delta)^{-1}M_{12} \qquad (17)$$

• The closed-loop system achieves nominal performance if the performance objective is satisfied for the nominal plant model, *Go*. In this problem, that is equivalent to the following form:

$$\left\| M_{22} \right\|_\infty < 1.$$

• The closed-loop system achieves robust stability if the closed-loop system is internally stable for all the possible plant models. In this problem, that is equivalent to a simple norm test on a particular nominal closed-loop transfer function:

$$\left\| M_{11} \right\|_\infty < 1.$$

• The closed-loop system achieves robust performance if the closed-loop system is internally stable for all the possible plant models, and in addition to that, the performance objective is satisfied:

$$\sup_\omega \mu(M) < 1 \Leftrightarrow \left\| \mu(M) \right\|_\infty < 1$$

The goal of the μ synthesis is to minimize over all stabilizing controllers *K*, the peak value $\mu_\Delta(.)$ of the closed loop transfer function *FL (P, K)*. The formula is as follows:

$$\min_K \sup_\omega \mu_\Delta[F_L(P,K)(j\omega)]$$

In this formula the block structure Δ is defined in the following form:

$$\Delta := \left\{ \begin{bmatrix} \Delta_1 & 0 \\ 0 & \Delta_2 \end{bmatrix} : \Delta_1 \in C^{1\times1}, \Delta_2 \in C^{3\times1} \right\} \subset C^{4\times2}$$

The first block of this structured set with input e and output d corresponds to the scalar-block uncertainty Δ_m which is used to model the uncertainty. The second block Δ_2 is a fictitious uncertainty block with input $\tilde{z}$ and outputs $\tilde{\varpi}$. This block is used to incorporate the $H\infty$ performance objective on the weighted output sensitivity transfer function into the μ-framework (Fig-3.2)

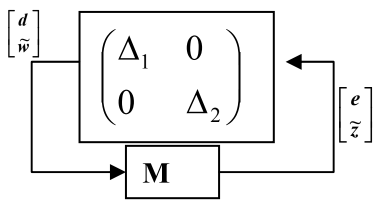

Figure3.2 Equivalent Robust Performance Problem.

At present, there is no direct method to synthesize a μ optimal controller, however, the D-K iteration, which combines μ-analysis and $H\infty$ synthesis yields good results. For a constant matrix M and an uncertainty structure Δ, an upper bound for $\mu_\Delta(M)$ is an optimally scaled maximum singular value: $\mu_\Delta(M) < \inf_{D \in D_\Delta} \bar{\sigma}[DMD^{-1}]$

Where $\boldsymbol{D_\Delta}$ is the set of matrices with the property that $D\Delta = \Delta D$ for every $D \in D_\Delta, \Delta \in \Delta$.

Using this upper bound, the optimization is reformulated as:

$$\min_K \sup_\omega \inf_{D_\omega \in D_\Delta} \bar{\sigma}[D_\omega F_L(P,K)(j\omega)D_\omega^{-1}] \qquad (18)$$

Where $\boldsymbol{D_\omega}$ is selected from the set of scaling $\boldsymbol{D_\Delta}$ independently of every ω. The optimization problem can be solved in an iterative way using for K and D. This is the so-called D-K iteration. It is performed with a two-parameter minimization in a sequential way, first minimizing over K with $\boldsymbol{D_\omega}$ fixed, then minimizing point wise over $\boldsymbol{D_\omega}$ with K fixed, etc. Although the joint optimization of D and K is not convex and the global convergence is not guaranteed, this approach works well, BALAS et al., (1991)[21]; PACKARD and DOYLE, (1993)[3]; ZHOU, (1996). [22].The synthesis of the observer is accomplished by solving D-K algorithm. The observer block diagram is shown in Fig-4.

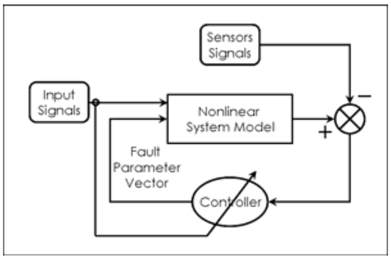

Figure 4. Observer Schema

VALIDATION AND SIMULATION RESULTS

Our Diesel Engine is equipped with two sensors that measure the rotational speed and the admission pressure. This application has two unknown inputs: the parameter fault, the resistive torque. The following figures represent fault simulations and the response of our FDE system for a reduction in admission process, for the remaining faults the simulation is similar. These simulations were carried out under Matlab/Simulink environment. All results demonstrate the effectiveness and the highly-satisfactory response of the proposed overall FDE system.

Figure- 5 simulates an admission reduction fault at t = 1s for an mf = 2 mg/sc and $Gv = 1$ plus none measured Cr =100 N.m.

Weighting function We is chosen as low pass filter thus this allow detection of low frequencies perturbations (faults) and filter high frequencies perturbations (noise).

By applying D-K algorithm on the augmented system we can achieve an H∞ norm of 0.1 between ω and $[e; e_y]$. Modulation uncertainties are simulated by executing "ultidyn" (Uncertain LTI Dynamics) function of Matlab in series with a filter that describes uncertainties percentage function of frequency .

Uncertainties on system begins at approximately 5 Hz and increases to 100% at approximately f = 50 Hz. External perturbations are simulated as an additive Gaussian noise to the measurements and to the simulated admission reduction factor as indicated in the following figure.

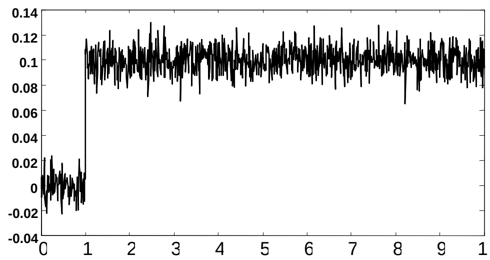

Figure 5. admission reduction factor of 10% at t=1sc .

By applying formula (14) on output D-K controller synthesized by the function « ***dksyn*** » of Matlab we can detect actuator fault parameter (admission reduction factor) while filtering Gaussian noises as indicated on Fig.6.

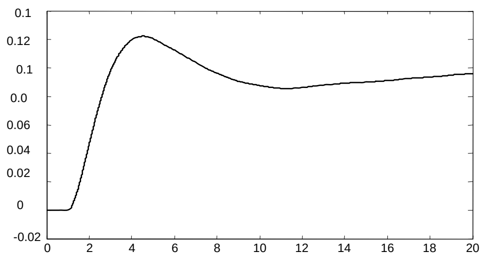

Figure 6. estimated admission reduction factor.

In order to test robustness performance we simulate the model for different uncertainties values which lead to the same parameter fault, also by applying "worst case" command of Matlab that calculate maximum gain, between perturbation and controlled vector, of the closed loop at a given frequency for all possible systems in the presence of uncertainties we can verify robustness of controller as illustrated in the following figure. (Fig-7)

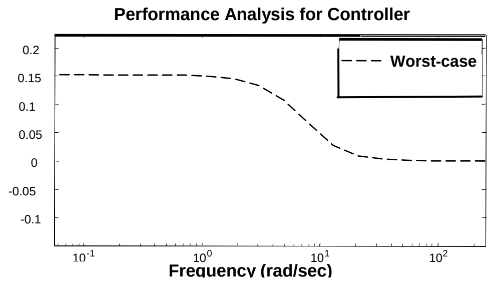

Figure 7. Performance Analysis

We remark that the Worst – case gain at a given frequency is less than 0.15 for all possible systems over all frequencies which is a sufficient attenuation that permit the error vector to approaches zero independently from perturbations.

6 CONCLUSION

In this paper, a H∞/μ FDE-filter technique has been applied to a nonlinear model of a Diesel engine. The proposed strategy endowed the overall system with the capability of detecting and isolating six faults in different part of the engine: intake, exhaust, turbo compressor, VGT.

REFERENCES

[1] Doyle, J.C., “Analysis of Feedback Systems with Structured Uncertainties,”IEE Proc., vol. 129, pt. D (1982), pp. 242–250.

[2] Fan, M.K.H., A.L. Tits, and J.C. Doyle,“Robustness in the Presence of Mixed Parametric Uncertainty and Unmodeled Dynamics,” IEEE Trans. Aut. Contr.,36 (1991), pp. 25–38.

[3] Packard A., and Doyle J.C., “The Complex Structured Singular Value,”Automatica, 29 (1994), pp. 71–109.

[4] Safonov M.G., “L1 Optimal Sensitivity vs. Stability Margin,” Proc. Conf.Dec. Contr., 1983.

[5] Stein G. and Doyle J.C., “Beyond Singular Values and Loop Shapes,” J.Guidance, 14 (1991), pp. 5–16.

[6] Frank P. M., & Ding X. (1997), "Survey of robust residual generation and evaluation methods in observer-based fault detection systems". Journal of Process Control, 7(6), 403–424.

[7] Patton R. J., & Chen J. (1997). Observer-based fault detection and isolation: Robustness and applications. Control Engineering Practice, 5(5), 671–682.

[8] Frank P. M., & Ding X. (1994). Frequency domain approach to optimally robust residual generation and evaluation for modelbased fault diagnosis. Automatica, 30(5), 789–804.

[9] Edelmayer, A., Bokor, J., & Keviczky, L. (1994). An HN filtering approach to robust detection of failures in dynamical systems. In 33rd IEEE conference on decision and control, Vol. 3. Lake Buena Vista, FL, USA (pp. 3037–3039).

[10] Mangoubi, R. S., Appleby, B. D., Verghese, G. C., & Vander Velde,W. E. (1995). A robust failure detection and isolation algorithm. In 34th IEEE conference on decision and control, New Orleans, USA, Vol. 3 (pp. 2377–2382).

[11] C. Ludwig, Mr. Ayoubi “Fault Detection Schemes for a Diesel Engine Turbocharger” proceedings of the American control conference ,seattle ,Washington,june 1995

[12] Lapuerta M., Armas O., Hernandez J.J. “Diagnosis of DI Diesel combustion from in-cylinder pressure signal by estimation of mean thermodynamic properties of the gas”. Control Engineering Practice 13 (2005) 189–203

[13] GEN-TING YAN, GUANG-FU MA “Fault Diagnosis of diesel engine combustion system based on neural networks” Proceedings of the Third International Conference on Machine Learning and Cybernetics,Shanghai,26-29 August 2004 IEEE 2004

[14] Raluca F. Constantinescu, Peter D. Lawrence, Phillip G. Hill “Model-Based Fault Diagnosis of a Two-Stroke Diesel Engine” IEEE 1995 Systems, Man and Cybernetics, 1995. Intelligent Systems for the 21st Centuryapos;., IEEE International Conference on Volume 3, Issue , 22-25 Oct 1995 Page(s):2216 - 2220 vol.3

[15] Mattias Nyberga, Thomas Stutteb “Model based diagnosis of the air path of an automotive diesel engine” IEEE 2003 Control Engineering Practice, Volume 12, Issue 5, 1 May 2004, Pages 513-525

[16] Keng Boon Goh, Sarah K. Spurgeon, N. Barrie Jones “Fault diagnostics using sliding mode techniques” Control Engineering Practice 10 (2002) 207–217

[17] R.Tafreshi, H.Ahmadi, F.Sassani, G.Dumont “Informative Wavelet Algorithm in Diesel Engine Diagnosis” IEEE International Symposium on intelligent Control Vancouver, Canada October 27-30, 2002

[18] YongHe and LeiFeng “Diesel Fuel Injection System Faults Diagnosis Based on Fuzzy Injection Pressure Pattern Recognition” Poceedings of the 5" World Congress on Intelligent Control and Automation, June 15-19, 2004, Hangzhou, P.R. China 2004 IEEE

[19] Zhang Y, Zhang Z., "The Identification Based on the Two Visual Measures for Ring Gumming Fault in Vehicle Diesel Engine", Vehicle Electronics Conference, 1999 Proceedings of the IEEE International Volume , Issue , 1999 Page(s):221 - 224 vol.1

[20] Doyle J. C., Glover K., Khargonekar P. P., Francis B. A. "State-Space Solutions to Standard H2 and H∞ Control Problems", IEEE Transactions on Automatic Control, 1989, Vol. 34/8, pp. 831-847

[21] Zhou K. "Robust and Optimal Control", Prentice Hall, New Jersey, 1996

[22] Balas G., Doyle J. C., Glover K., Packard A., Smith R. "μ Analysis and Synthesis Toolbox", MUSYN Inc. and The Mathworks Inc., 1991.

[23] X. Dovifaaz, “Modélisation et commande de moteur Diesel en vue de la réduction de ses émissions”. PHD thesis, UPJV, Amiens, France, 2001.

[24] R. Omran, R. Younès, “Genetic Algorithm for Dynamic Calibration of Engine's Actuators” SAE paper 2007-01-1079.