# Structured hypothesis tests based diagnosis : application to a common rail diesel injection system

Zahi SABEH, José RAGOT, Frédéric KRATZ
Delphi Diesel Systems, Centre Technique de Blois
*9 boulevard de l'Industrie, 41042 Blois*
*zahi.sabeh@delphi.com*
Centre de Recherche en Automatique de Nancy, INPL
*2 avenue de la Forêt de Haye, 54516 Vandoeuvre les Nancy*
*Jose.Ragot@ensem.inpl-nancy.fr*
Laboratoire de Vision et Robotique, Université d'Orléans, IUT de Bourges
*63 avenue de Lattre de Tassigny, 18020 Bourges*
*Frederic.Kratz@bourges.univ-orleans.fr*

**Abstract :** common rail injection system has been developed to increase diesel engine performances and to reduce noise, emission and fuel consumption. Such goals are possible only if the whole system is perfectly controlled. But, any system component failure can lead to significant engine performances decrease and degraded emission control.
A faults diagnosis system based on structured hypothesis tests is proposed in this paper, in order to detect and isolate different types of failures which are able to affect the pressure control loop in a common rail diesel injection system.

**Keywords :** common rail injection system, diagnosis, faults detection, faults isolation, structured hypothesis tests, modeling.

## 1 Introduction

The key feature of the common rail injection system is that the injection pressure is generated independently of engine speed and injected fuel flow.
This characteristic property presents new horizons for air/fuel mixture preparation and injection process control because, from now on, the injection pressure will be freely realizable in the cartography.
Several mechanical, electromagnetic and electronic components (pump, electro valve, sensor…) contribute to generate and control the injection pressure which reaches around 1400 bars.
Any drift or failure in one of these components implies predictably a modification of generated pressure level.
This modification influences naturally the injection process and move consequently the engine performances and emission out of their optimal areas.
Considering the previous effects, a diagnosis system becomes essential in order to detect as early as possible eventual failures in the pressure loop and to suggest recovery actions.
Model based fault diagnosis has gained increased interest during the last ten years thanks to technological advances of the on-board electronic control units, and increased demand on diagnosis performance in many areas.
Many studies have been devoted to diagnosis theory using models and analytical redundancy techniques [1][2][3].
Several research works have been performed in this field, on diesel engines in particular.
Some methods consist in training neural nets based models [4][5][6] with cylinder pressure, vibration and instantaneous speed sensors data of a diesel engine in order to detect and identify several types of failures having different signatures.
Interesting results have been also presented in [7][8].
They processed different types of faults in the intake and supercharging air paths of an automotive turbocharged diesel engine.
This is the reason why we here suggest a model based diagnosis method using structured hypothesis tests.
Both the framework and the basic principles of the method are summarized in Section 2.
Afterwards, we describe in Section 3 the process to which the suggested method will be applied.
Finally, the diagnosis system construction as well as some method application results will be shown in Section 4.

## 2 Model based diagnosis using structured hypothesis tests

We have chosen, in our case, a diagnosis system based on the structured hypothesis tests presented in [9] and shown in Figure 1.

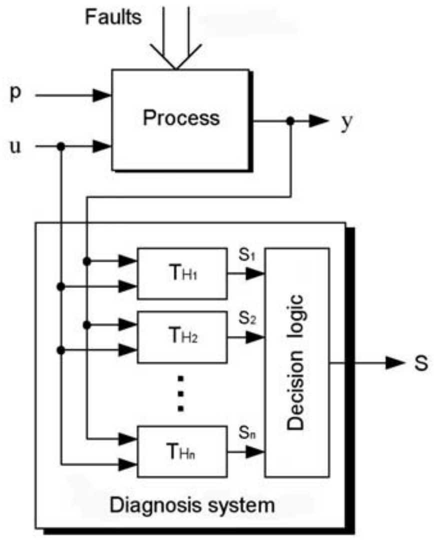


Figure 1 : Structured hypothesis tests based diagnosis system

The inputs to the diagnosis system is the process input *u* and the process output *y*.
The signal *p* represents inputs that are unknown to the diagnosis system, e.g. disturbances.
The output of the diagnosis system is the diagnosis statement *S* which contains information about which fault modes that can explain the behavior of the process.
This fault mode can correspond to either the presence of one or several faults *Fn*, or no fault status *NF* as a special case.
The null hypothesis $H_i^0$ means that the system fault mode, present in the process, belongs to a specific set of system fault modes $M_i$.
Otherwise, if hypothesis $H_i^0$ is rejected, the alternative hypothesis $H_i^1$ is confirmed, which means that the present fault mode does not belong to $M_i$, it belongs to complementary sets denoted $M_i^C$ :

$H_i^0 : \quad F \in M_i$

$H_i^1 : \quad F \in M_i^C$

Thus, each separate hypothesis test $T_{H_i}$ contributes with a piece of information $S_i$, corresponding to a certain set of system fault modes $M_i$, to the final diagnosis result.
So, the diagnosis system consists of a set of hypothesis tests $T_{H_i}$ and a decision logic which combines information to form the diagnosis statement *S*.
The simple intersection operation is mostly used for decision logic.
The diagnosis statement *S* then becomes a set of fault modes that can be expressed as :

$$S = \bigcap_i S_i = \bigcap_i M_i^C \quad (1)$$

Generally, the studied process contains several components (sensor, actuator…).
For each of these components, a number of fault modes can be also distinguished.
Each component *i* has a, possibly vector-valued, parameter $\theta_i$ which determines the exact fault mode (which can be no fault) of the component *i*.
All parameters $\theta_i$ are then grouped in a vector $\theta = [\theta_1, ... \theta_p]$ which describes a global fault mode of the whole process containing *p* components.
We consider in this study a single fault-mode process. Which means that only one fault mode can be present. This assumption is considered for both process and components.
Therefore, for each process fault mode, only one single hypothesis test must be evaluated.
For each hypothesis test we need to find a test quantity and a rejection region.
The sample data for each hypothesis is :

$$x = \begin{bmatrix} u(1) & u(2) & ... & u(N) \\ y(1) & y(2) & ... & y(N) \end{bmatrix}$$

The test quantity chosen for each hypothesis is a function from the sample data $x$ expressed as :

$$T_i(x) = \min_\theta V_i(\theta, x) \quad (2)$$

where $V_i(\theta, x)$ is a measure measuring the validity of the process model $M(\theta)$ with respect to the sample data $x$.
Thus, for a parameters vector $\theta$, the calculation of the test quantity $T_i$ can be viewed as a minimization problem of $V_i(\theta, x)$ using the sample data $x$.
A threshold $J_i$ is associated to each test quantity $T_i$ in order to define the rejection region of null hypothesis $H_i^0$ as follows :

$T_i(x) \geq J_i$ : $H_i^0$ rejected ( $H_i^1$ accepted) (3a)

$T_i(x) < J_i$ : $H_i^0$ not rejected (3b)

This means that we need to design a test quantity $T_i(x)$ such that it is low if the data $x$ match the hypothesis $H_i^0$, i.e. a fault mode in $M_i$ can explain the data. Also if the data come from a fault mode not in $M_i$, $T_i(x)$ should be large.

## 3 Common rail diesel injection system

### *3.1 Process description*

In this study framework, we are interested particularly in the pressure control loop of a common rail diesel injection system.
In this system, the pressure is generated thanks to high-pressure pump (see Figure 2) driven by the engine camshaft.

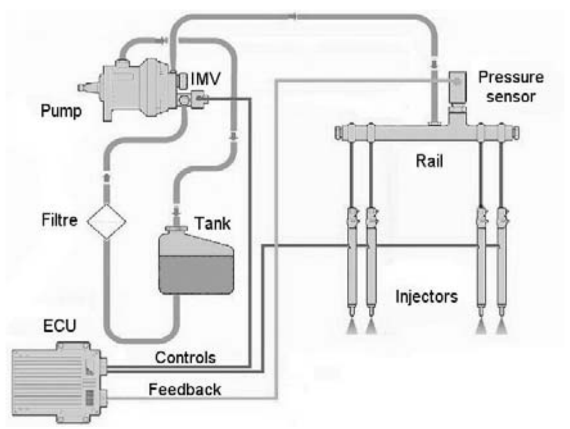


Figure 2 : Common rail diesel injection system

A filling actuator « IMV : Inlet Metering Valve » mounted on the pump, with electrically controllable cross section area, allows to modulate the generated pressure which is stocked into a high-pressure accumulator (the rail).
Pressurized fuel is then led to the injectors that allow to spray this fuel into the engine combustion chambers.
A pressure sensor is mounted on the rail in order to measure instantaneously the current pressure level in this accumulator.
Finally, an on-board electronic control unit evaluates pressure sensor signals and keep the pressure in the rail at a desired level by controlling the IMV actuator and injectors.
The ECU manages the injection process and supervises also the correct functioning of the injection system as a whole.

### *3.2 Modeling*

The discrete model of the pressure control process described previously can be given, for the fault-free case (no faults are present), after normalization by the following equations :

$$\begin{aligned} X_1(k+1) = X_1(k) + T_e[c_1 P(X_2(k))X_3(k) \\ - c_2 X_2(k)u_2(k) - c_3 X_1^{1.88}(k) \\ - c_4\sqrt{X_1(k)}u_4(k)] \end{aligned} \tag{4}$$

$$\begin{aligned} X_2(k+1) = X_2(k) + T_e[c_5 u_2(k) - c_6 u_3(k) \\ - c_7 X_2(k)] \end{aligned} \tag{5}$$

$$\begin{aligned} X_3(k+1) = X_3(k) + T_e[-c_8 X_3(k) \\ + c_9 u_1(k) + c_{10}] \end{aligned} \tag{6}$$

where :
$X_1, X_2, X_3$ states represents respectively rail pressure, engine speed and cross section area of IMV actuator. In the studied process, only $X_1, X_2$ states are measurable.
The $u_1, u_2, u_3, u_4$ inputs are respectively : the current through IMV actuator coil, injected fuel flow into the cylinders, resistant torque exerted on engine (unknown *a priori*) and the discharge command applied to injectors (without injection into the cylinders).
$T_e$ is the sample time period, *P* is a 2nd degree polynomial and $c_i\ (i = 1,...,10)$ are constants.
The rail pressure control is performed by using $X_1$ state measurements coming from rail pressure sensor, and by applying $u_1$ command signal to IMV actuator in order to modulate the generated pressure.
Figure 3 shows a simulation example of the process described by equations (4),(5) and (6) in fault-free case.
This figure includes also the accelerator-pedal position representing a certain driving cycle.

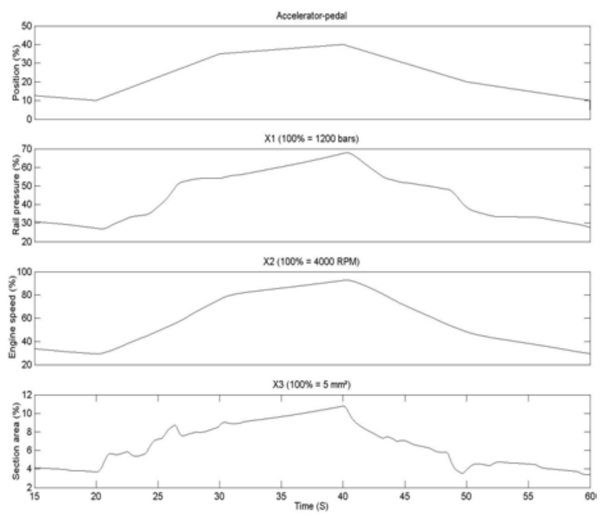


Figure 3 : Fault-free pressure control process simulation

# 4 Construction of the diagnosis system

We develop, in this section, some examples of diagnosis using structured hypothesis tests applied to the studied pressure control process.
So, we are interested in the component fault modes described in the following table :

| Index | Component | Fault mode |
|---|---|---|
| C | Pressure sensor | NF: no fault<br>$C_b$ : signal bias<br>$C_g$ : transfer gain modification |
| A | Filling actuator | NF: no fault<br>$A_d$ : cross section area drift |

Therefore, we can define the hypotheses which must be tested with associated process fault modes as :

$$H_{NF}^{0} : F \in M_{NF} = \{NF\}$$
$$H_{NF}^{1} : F \in M_{NF}^{c} = \{C_b, C_g, A_d\}$$
$$H_{Cb}^{0} : F \in M_{Cb} = \{C_b, NF\}$$
$$H_{Cb}^{1} : F \in M_{Cb}^{c} = \{C_g, A_d\}$$
$$H_{Cg}^{0} : F \in M_{Cg} = \{C_g, NF\}$$
$$H_{Cg}^{1} : F \in M_{Cg}^{c} = \{C_b, A_d\}$$
$$H_{Ad}^{0} : F \in M_{Ad} = \{A_d, NF\}$$
$$H_{Ad}^{1} : F \in M_{Ad}^{c} = \{C_b, C_g\}$$

in order to determine parameters vector $\theta$ which defines the studied fault modes, we suggest the following fault models :

<u>Sensor faults model :</u>

$$X_{1m}(k) = gX_{1p}(k) + b + v_1(k) \qquad (7)$$

where $X_{1m}$ is the measured rail pressure,
$X_{1p}$ is the predicted rail pressure which is calculated thanks to process model described by equations (4), (5) and (6).
$\theta_C = [g, b]$ is the parameters vector defining pressure sensor fault modes described in the above table.
$v_1$ is a signal that represents a gaussian distributed measurement noise with a null mean value.

<u>Actuator faults model :</u>

$$\begin{aligned} X_{1m}(k) = {} & X_{1m}(k-1) \\ & + T_e[c_1 P(X_{2m}(k-1))(X_3(k-1) + d) \\ & - c_2 X_{2m}(k-1)u_2(k-1) - c_3 X_{1m}^{1.88}(k-1) \\ & - c_4 \sqrt{X_{1m}(k-1)}u_4(k-1)] + v_2(k) \end{aligned} \qquad (8)$$

where $X_3$ is the IMV cross section area calculated by equation (6) and derived from fault-free case process model.
$X_{2m}$ is the measured engine speed.
$\theta_A = [d]$ is the parameters vector defining IMV fault modes described in the previous table.
$v_2$ is a signal that represents a gaussian distributed measurement noise with a null mean value.
Thus, the parameters vector defining process fault modes becomes : $\theta = [g, b, d]$.

As shown in Section 2, in order to evaluate the hypothesis tests defined previously in this section, we must determine for each hypothesis a test quantity and a rejection threshold as described by equations (2), (3a) et (3b).
The following test quantity, based on prediction error, suggests a process validity measure with respect to sample data $x$ as :

$$T_i(x) = \min_{\theta_i} \frac{1}{N} \sum_{k=1}^{N} \left(X_m(k) - X_p(k)\right)^2 \qquad (9)$$

where $X_m \in \mathbb{R}^N$ is the studied state measurements vector, $X_p \in \mathbb{R}^N$ is the state predictions vector which takes into account fault parameters vector $\theta_i$.

### *No fault {NF}*

This fault mode, corresponding to process fault-free case, can be defined by parameters vector $\theta_{NF} = [1,0,0]$.
The associated test quantity is expressed by the following equation :

$$T_{NF}(x) = \frac{1}{N} \sum_{k=1}^{N} \left(X_{1m}(k) - X_1(k)\right)^2$$

Rejection threshold can be determined in the process fault-free case as follows :

$$J_{NF} = \max\left[T_{NF}(x_1), \ldots, T_{NF}(x_j)\right]$$

where $x_1, \ldots, x_j \in \mathbb{R}^{5xN}$ are the different data samples used, including measurable states $X_1, X_2$ as well as the commands $u_1, u_2, u_4$.

### *Signal bias {Cb}*

This fault mode is defined by a pressure sensor output signal bias.
The parameters vector that corresponds to this fault mode becomes : $\theta_{Cb} = [1, b, 0]$, and the associated test quantity is the following :

$$T_{Cb}(x) = \frac{1}{N} \sum_{k=1}^{N} \left( X_{1m}(k) - X_1(k) - \hat{b}(x) \right)^2$$

with :

$$\hat{b}(x) = \frac{1}{N}\sum_{k=1}^{N}\left(X_{1m}(k) - X_1(k)\right)$$

the estimated bias that minimizes $T_{Cb}$ considering data sample $x$.

Rejection threshold of this fault mode, for a process without faults, can be given similarly as :

$$J_{Cb} = \max\left[T_{Cb}(x_1),...,T_{Cb}(x_j)\right] \ , \ x_1,...,x_j \in \mathbb{R}^{5xN}$$

### *Transfer gain modification {Cg}*

This fault mode occurs when an extra gain is applied to pressure sensor output signal, modifying in this way the global sensor transfer gain.

Thus, the fault parameters vector becomes : $\theta_{Cg} = [g,0,0]$, and the corresponding test quantity is :

$$T_{Cg}(x) = \frac{1}{N}\sum_{k=1}^{N}\left(X_{1m}(k) - \hat{g}(x)X_1(k)\right)^2$$

with :

$$\hat{g}(x) = \frac{X_1^T}{X_1^T X_1} X_{1m}$$

the least square estimate of $g$ that minimizes $T_{Cg}$ considering data sample $x$.

Rejection threshold of this fault mode, for a process without faults, can be expressed as : $J_{Cg} = \max\left[T_{Cg}(x_1),...,T_{Cg}(x_j)\right] \ , \ x_1,...,x_j \in \mathbb{R}^{5xN}$

### *Cross section area drift {Ad}*

The fault mode, in this case, comes as a bias in the cross section area of filling actuator (IMV). This may occur because of impurity crossing through the high pressure pipes (négative bias in this case).

the fault parameters vector then becomes : $\theta_{Ad} = [1,0,d]$, and the associated test quantity is :

$$T_{Ad}(x) = \frac{1}{N}\sum_{k=1}^{N}\left(X_{1m}(k) - X_{1p}(k)\right)^2$$

where $X_{1p}$ is the rail pressure predictions vector which takes into account the cross section area drift. $X_{1p}$ calculation is based on equation (8) as follows :

$$\begin{aligned} X_{1p}(k+1) = X_{1p}(k) + T_e\Big[ & c_1 P(X_{2m}(k))\left(X_3(k) + \hat{d}(x)\right) \\ & - c_2 X_{2m}(k)u_2(k) - c_3 X_{1p}^{1.88}(k) \\ & - c_4\sqrt{X_{1p}(k)}u_4(k) - c_4\sqrt{X_{1p}(k)}u_4(k) \quad \Big] \end{aligned}$$

with : $k = 2,...,N$ et $X_{1p}(1) = X_{1m}(1)$

$\hat{d}(x)$ is the least square estimate of cross section area drift that minimizes $T_{Ad}$ considering data sample $x$.

Rejection threshold of this fault mode for a process without faults is :

$$J_{Cg} = \max\left[T_{Cg}(x_1),...,T_{Cg}(x_j)\right] \ , \ x_1,...,x_j \in \mathbb{R}^{5xN}$$

Figure 4 shows application results of the three following fault modes :

- pressure sensor abrupt transfer gain modification of 10% during the period *t* = [25,28] *s*.
- pressure sensor abrupt output signal bias of 5% during the period *t* = [40,43] *s*.
- filling actuator abrupt cross section area drift of -4% since *t* = 50 *s*.

with data samples width *N* = 64, and sample time period $T_e$ = 4 *ms*. Rejection thresholds are fixed to :

$$J_{Cg} = 0.03, \quad J_{Cb} = 0.02, \quad J_{Ad} = 0.008, \quad J_{NF} = 0.1$$

The process faults diagnosis can be then performed by using the following incidence structure :

| | NF | Cb | Cg | Ad |
|---|---|---|---|---|
| $TH_{NF}^0$ | 1 | 0 | 0 | 0 |
| $TH_{Cb}^0$ | 1 | 1 | 0 | 0 |
| $TH_{Cg}^0$ | 1 | 0 | 1 | 0 |
| $TH_{Ad}^0$ | 1 | 0 | 0 | 1 |

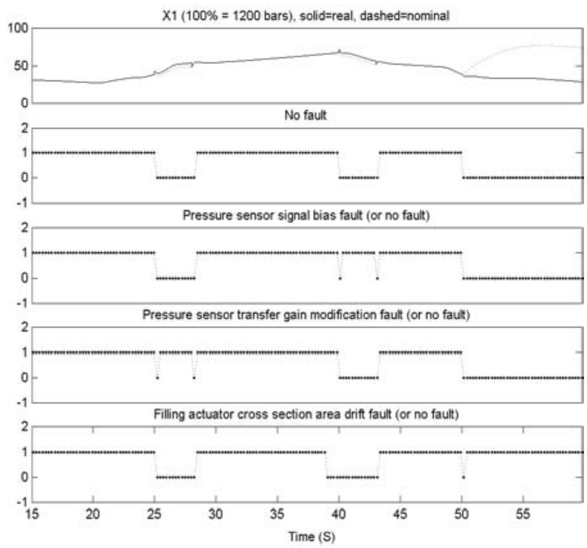


Figure 4 : Results of hypothesis tests applied to a faulty pressure control loop

Examples :
- as shown in Figure 4, when $t$ = 28 $s$, we have : $TH_{NF}^{0} = 0, TH_{Cb}^{0} = 0, TH_{Cg}^{0} = 1, TH_{Ad}^{0} = 0$ .
Using above incidence structure, we deduce that the present failure corresponds to a pressure sensor transfer gain modification fault (Cg).

- when $t$ = 55 $s$, looking at the same figure, we have : $TH_{NF}^{0} = 0, TH_{Cb}^{0} = 0, TH_{Cg}^{0} = 0, TH_{Ad}^{0} = 1$ .
This leads us to conclude, taking into account the associated incidence structure, that the present failure is a filling actuator cross section area drift fault (Ad).

# 5 Conclusion

A diagnosis system based on structured hypothesis tests has been presented in this paper.
The aim of this diagnosis system is to detect and isolate several failure types which are able to affect the pressure control loop of a common rail diesel injection system.
The physical process as well as the failures intended to be detected by diagnosis have been modeled and studied.
The application results of the diagnosis system have shown that it was possible to detect and isolate sensor and actuator failures in the high-pressure control loop of the injection system.
This shows clearly the strength and the high potential of the method which is able to cover a large variety of process failures and components.
Other research works are in progress in order to study and evaluate the influence of different types of noise on structured hypothesis tests based diagnosis system robustness and performances.
More high-pressure loop actuators are also intended to be covered by the diagnosis system developed in this study framework.

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