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Neuro Fuzzy Modelling of a Dci Diesel Engine and Fault Detection and Diagnosis by Space Parity and Observers

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Abstract: Faults detection and diagnosis systems, which are designed and implemented for the common rail direct injection diesel engine. Requiring models that are very near to the mechanical and thermodynamic reality process which is substantially non linear and time varying. A complete model is presented, the parameters identification using neuro-fuzzy approach, the around this model, we have built a faults diagnosis and detection structure, using the parity space and the observers. Finally, we propose a human machine cooperation structure in the monitoring loop, in order to have more reliability and an easier intervention for this process maintenance.

Key words: Fault detection, diagnosis, modelling, LOLIMOT identification, parity space, observer, simulation interface, cooperation human machine

INTRODUCTION

HIS work was initiated to answer certain questions concerning the right operation of the common rail and direct injection diesel engine, (DCI, HdI, model).

The technological complexity of the elements which constitute these engines, increasingly integration of calculation space and as well as the degree of cooperation of the designer detection of rather powerful diagnosis of faults.

For that it is presented a complete model describing the phases of admission combustion and of exhaust, model strongly non linear.

The neuro-fuzzy approach is used to build multi model (LOLIMOT) 'local linear model tree' the aforementioned reproduce the most accurately phenomenon of thermodynamic and mechanic.

The identification of the parameters is carried out on uncoupled linear models described by a neuro-fuzzy representation see ref[1-3].

A rather consistent simulator is launched for to build a data base, permitting to delimit the operation horizons, of direct injection engine.

A structure of detection of faults and diagnosis is built around a block of generator of residues by two methods, that of the parity space and a bank of observers, in a second stage we established a test to compare the residues with the normal value, thus we can conclude if the process is faulty.

MODELLING OF COMMAN RAIL DIRECT INJECTION DIESEL ENGINE

The system of injection high pressure with common consists in feeding, using an electronically controlled high Pressure pump, a commonrail which provides the function of accumulator of the fuel. This rail is connected to injectors which ensure a very fine pulverization

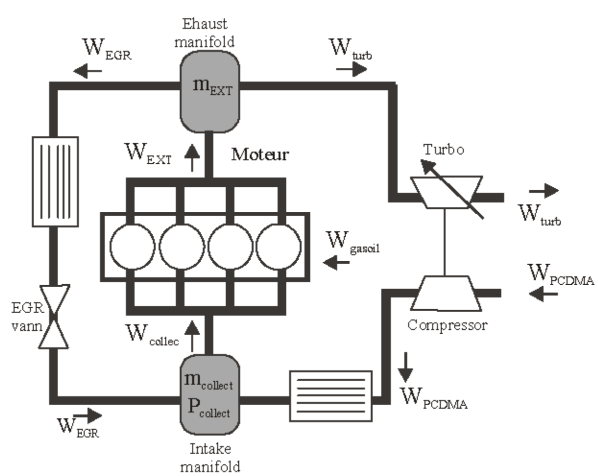

Fig. 1: Simplified diagram of the diesel engine

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Table 1: Units for state space represntation

Variable	Symbol	Description
u1	x_{egr}	Egr rate
u2	m_f	fuel mass flow
u3	x_{vtg}	Varying Turbin geometry
u4	M_{laod}	The load momentum
x1	n	Speed engine
X2	Pman	Intake Manifold pressure
X3	mff	Fuel film mass flow
X4	PC	Power of turbo
X5	Pex	I Exfaust manifold pressure
X6	Tman	Intake manifold temperature
X7	Texo	Exfaust manifold temperature

directly in the combustion chamber using a pressure ranging between 1350 and 1400 bars. This very fine and Mégane 2. Pulverization makes it possible to improve the combustion we are particularly interested in the study of the Renault engine 1,5 DCI (K9K) of the CLIO, Kangoo

The physical model representing the dci diesel engine includes the following dynamics:

- Dynamics of the air represented by the equations: 2, 4 and 6. of (∑)
- Dynamics of combustion equations 1 and 3. of (∑)
- Dynamics of the exhaust equation 5 and 7.de (∑)

$$\dot{x}_1 = \left(\frac{60}{2\times\pi\times I_{tot}}\right)\times\left(\left(\frac{n_{fc}\times Q_{lhv}}{2\times\pi\times 60}\right)\times\frac{((1-X)\times u_2 + x_3)}{x_1} - M_{fric}(x_1,x_2) - u_4\right)$$

$$\dot{x}_2 = \frac{R\times x_6}{V_{man}\times 3600}(\dot{m}_a + \dot{m}_{egr} - \dot{m}_T)$$

$$\dot{x}_3 = \frac{1}{T_{ff}}(X\times u_2 - x_3) \qquad (\Sigma$$

$$\dot{x}_4 = \frac{1}{T_0}(tt\times P_t - x_4)$$

$$\dot{x}_5 = \frac{R\times x_6}{V_d\times 3600}(u_2 - \dot{m}_{exo} - \dot{m}_{egr} + \dot{m}_T)$$

$$\dot{x}_6 = \frac{\left(\dot{m}_a\times(\gamma\times t_{2b} - x_6) + (\dot{m}_{egr}\times(\gamma\times T_{egr} - x_6)) - (\dot{m}_T\times(1-\gamma)\times x_6)\right)\times R\times x_6}{V_{man1}\times x_2}$$

$$\dot{x}_7 = \frac{\left((u_2 + \dot{m}_T)(\gamma\times x_7 - x_7) - (\dot{m}_{egr} + \dot{m}_{exo})(\gamma\times x_7 - x_7)\right)\times R\times x_7}{V_{man}\times x_2}$$

It is has to stress that the input signals (which will be to use in the phase training of ' lolimot ' are of pseudo random binary type, Fig. 2. One uses the method Rang-Kutta of order 4 for the solution of the nonlinear system of equations composed by the equations (∑) x1... x7.

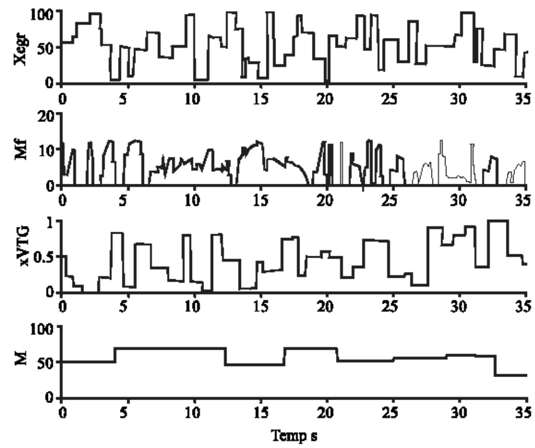

Fig. 2: The inputs of the system, Rate of egr, flow of injection, variable geometry harnesses, the moment of load

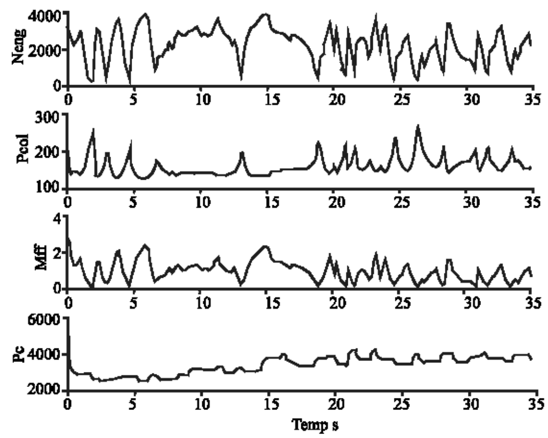

Fig. 3: Speed, pressure of admission, flow of films injection, power of turbo

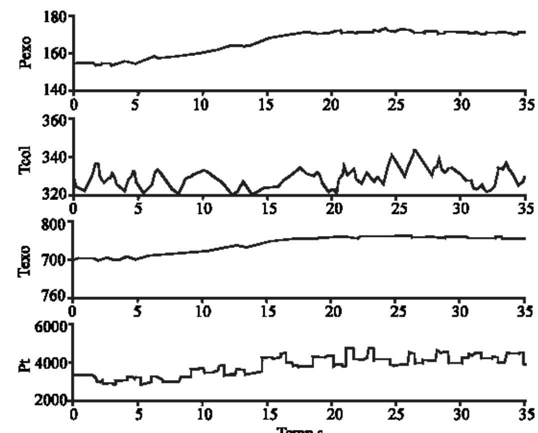

Fig. 4: Pressure of exhaust, temperature of admission, temperature of exhaust

The solution of the system is represented in Fig. 3 and 4, it corresponds to the variables of state of the system (driving).

USE OF NEURO-FUZZY NETWORKS LINEARIZATION OF THE MODEL IN ORDER TO OBTAIN (LOLIMOT)

The dynamic models with p input and Q are represented by the structure of NARX (i = 1....,q) outputs:

$$\begin{aligned}\hat{y}_i(k) = f_i(\ & u_1(k-1),\cdots,u_1(k-nu_1),\cdots,\\ & u_p(k-1),\cdots,u_p(k-nu_p),\\ & y_1(k-1),\cdots,y_1(k-ny_1),\cdots,\\ & y_p(k-1),\cdots,y_p(k-ny_p))\end{aligned} \quad (1)$$

where nu_i and ny_i are the dynamic order of the system.

The structure of the model which is represented in (1) carries out a stage of prediction ahead for the identification of the parameters, the model can be carried out in parallel with the process (simulation) while turning over the outputs of models of prediction $\hat{y}_i$ instead of employing the measurements produced by process, e.g. they are normalized such:

$$\sum_{i=1}^{M}\Phi_i(z) = 1 \quad (2)$$

The structure of the local linear network neuro-fuzzy is represented in Fig. 5. Each neuron carries out a Linear Model Local (LLM) and is associated to a function of validity which determines the area built of the validity of the LLM.

The use of the network of neuro-fuzzy for the linearization of model For every input Z of model, the output of local linear model neuro-fuzzy is calculated by:

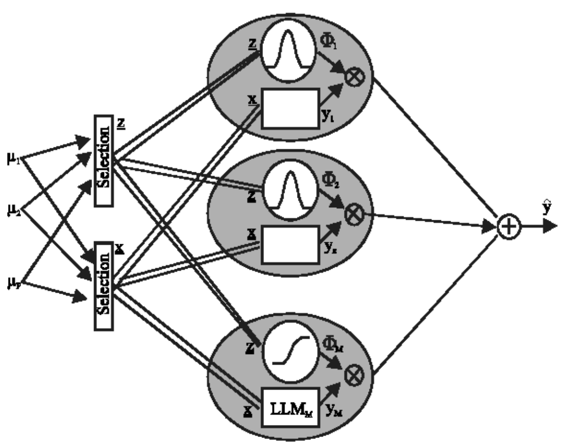

Fig. 5: Fuzzy Structure of neuro fuzzy network of local linear model with M neurons for N_X LLM of inputs X and N_Z functions of validity of inputs Z

$$\hat{Y} = \sum_{i=1}^{m}(w_{i,0} + w_{i,1}x_1 + w_{i,2}x_2 \cdots + w_{i,nx}x_{nx})\,\Phi_i(\underline{z}) \quad (3)$$

Where the local linear models depend on $\underline{x} = [X_1\ X_2\ X_3 \ldots X_N]^T$ and the functions of validity depend on $\underline{z} = [Z_1\ Z_2\ Z_3\ \ldots, Z_N]^T$ Thus, the output of network is calculated as a balanced sum of outputs of the local linear models where $\Phi_i(\underline{z})$ are interpreted as operation point depend on ponderation . The network interpolates between different LLMs with the validity functions. The weights W_i are linear parameters of network.

The functions of validity are typically selected as normalized Gaussienne. If these Gaussianne are moreover orthogonal the functions of validity are defined by the following equations:

$$\Phi_i(\underline{z}) = \frac{\mu_i(\underline{z})}{\sum_{j=1}^{m}\mu_j(\underline{z})} \quad (4) \qquad (4)$$

with:

$$\mu_i(z) = \exp\left(-\frac{1}{2}\left(\frac{(z_1-c_{i,1})^2}{\sigma_{i,1}^2} + \cdots + \frac{(z_{nz}-c_{i,nz})^2}{\sigma_{i,nz}^2}\right)\right) \quad (5)$$

The centres and the standard deviations are the nonlinear parameters of the network.

In the fuzzy interpretation of system, each neuron represents a rule. The functions of validity represent the positions of rule and LLMs represents consequent of rules.

Unidimensional Gaussienne membership functions:

$$\mu_{i,j}(z_j) = \exp\left(-\frac{1}{2}\frac{(z_j-c_{i,j})^2}{\sigma_{i,j}^2}\right) \quad (6)$$

We can be combined by a T-standard (conjunction) carried out with the operator of product to form the functions of multidimensional membership represented in (5).

One of the principal forces of the linear local neuro-fuzzy models is that the antecedents and the consequents must not depend on the identical variables, meaning $\underline{z}$ and $\underline{x}$ can be selected independently[4,5].

TECHNIQUES OF DETECTION AND DIAGNOSIS OF THE FAULTS

The techniques of detection of the fault are numerous, we can classify in distinguish four principal techniques:

- Methods by material redundancies,
- Methods by expert systems,
- Methods by pattern recognition,
- Analytic methods (based on analytic models)

In our study we are interested by the last method. In fact the comparison Between two methods which we judged adapts to know parity space and a banc of observers, we shall proposed a structure F.D.I around the block of residues generation who will take account of the faults sensors, actuators and system. Study in simulation is made on this part which be appeared the faults in all element of system[6,7].

The parity space: The concept of the space parity was generalized by using the relation temporal of redundancy (or dynamics) generated from the model of the dynamic system let us consider the following deterministic model:

$$\begin{cases} x(k+1) = A\,.x(k) + B\,u(k) + F_1\,d(k) \\ y(k) = C\,x(k) + F_2\,d(k) \end{cases} \quad (7)$$

Meaning that the measurements depend only defected state on defect and does not utilize the input U.

$X \in lR^N$ the unknown state; $U \in lR^R$ the known input.
$y \in lR^N$ known outputs. $C \in lR^{m.n}$ $F_1 \in lR^{n.p}$
With $\in$ lR: The matrix of state of system.
$F_2 \in lR^{m.p}$
$B \in lR^{n.r}$ the matrix of control

The material redundancy is expensive and offer small interest for the monitoring of the actuators, therefore we can regulate it by a temporal redundancy (dynamic) which links information of the sensors and the actuators at various moments, this redundancy offers a great help.

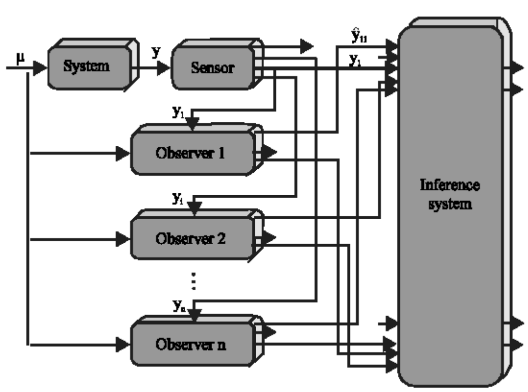

Fig. 6: Detection by a banc of observers

Indeed on a horizon of observation [K, k+s], the equations of system can be gathered in the form:

$$\begin{pmatrix} y(k) \\ y(k+1) \\ \vdots \\ \vdots \\ y(k+s) \end{pmatrix} = \begin{pmatrix} C \\ CA \\ \vdots \\ \vdots \\ CA^s \end{pmatrix} x(k) + \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ CB & 0 & & & \\ CAB & CB & \ddots & & \\ \vdots & \vdots & & \ddots & \\ \vdots & \vdots & & CB & \\ CA^{s-1}B & CA^{s-2}B & \cdots & CAB\ CB & 0 \end{pmatrix} \begin{pmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+s) \end{pmatrix} +$$

$$\begin{pmatrix} F_2 & 0 & 0 & \cdots & 0 \\ CF_1 & F_2 & & & \\ CAF_1 & CF_1 & \ddots & & \\ \vdots & \vdots & & \ddots & \\ \vdots & \vdots & & & \\ CA^{s-1}F_1 & CA^{s-2}F_1 & \cdots\cdots & CF_1 & F_2 \end{pmatrix} \begin{pmatrix} d(k) \\ d(k+1) \\ \vdots \\ d(k+s) \end{pmatrix} \quad (8)$$

One can write:

$$Y(k, s) = O(s).\ x(k) + G(s).\ U(k, s) + F(s).\ D(k,s) \quad (9)$$

One can indeed show the relation (9). Iteratively the relation is checked for S = 0, S = 1, one supposes that it is true for S and shows that it is true for s+1.

The form (9) is preferable to the form (8) because we passes from a system of N equations to a system of n(s+1) equations this offers more possibilities of the elimination of the unknown states x(k). For this elimination one multiply (9) by a matrix Ω (called matrix of parity) orthogonal to O (s) (the existence of Ω is related to the rank of O(s)). Ω. O (s) = 0 the generalized parity vector

$$\begin{aligned} &P(k) = \Omega(Y(k,s) - G(s).U(k,s)) \\ &\text{ou} \qquad\qquad\qquad\qquad (10) \\ &P(k) = \Omega\,F(s).\,D(k,s) \end{aligned}$$

The vector of parity generalizes P(k) characterizes all the existing relations between the inputs and the outputs of the systems.

This vector of parity is biased (after a failure of a sensor or an actuator), for example: the vector of parity becomes different from zero and is directed in a privileged direction according to the defect.

The temporal redundancy (dynamic) relating to only one sensor is related to a generator of relations expressing in the course of time the output of only one sensor, for that it is enough to extract the J^{3rd} component from the vector from observation by selecting in C the line C_J therefore (9) implies:

$$y_J(k,s) = O_J(s).\ x(k) + G_J(s).\ U(k,s) + F_J\ D(k,s) \qquad (11)$$

or: O_J G_J F_J result from the definition from O G and F by replacing C and by their J [3rd] line.

In case if Ω_J is an orthogonal matrix with O_J (s) thus the single relation of parity relating to the J3rd sensor is defined by:

$$P_J(k) = \Omega_J(y_J(k,s) - G_J(s).\ U(k,s)) \qquad (12)$$

for more precision the application of theorem of Cayley Hamilton implies the existence of a value S_J such as:

$$\text{if } s < S_J \rightarrow \text{row}(O_J(S)) = 1+s$$
$$\text{if } S = S_J \rightarrow \text{arrange}(O_J(s)) = S_J$$

as the line (S_J +1) of the matrix O_J (S_J is a linear combination of the other S_J lines there is a vector line Ω_J such as:

$$\Omega_j \cdot \begin{pmatrix} C_j \\ C_j A \\ \vdots \\ C_j A^{Sj} \end{pmatrix} = 0 \qquad (13)$$

$$P_J(k) = \Omega_J(y_J(k,s_J - g_J(S_J\ U(k, S_J)) \qquad (14)$$

the Eq. 12 which utilizes only one output of the system clarifies the temporal redundancy between the outputs and the J [rd] output and thus a means of test of correct operation of J [rd] sensor if one makes the assumption of correct operation of actuations of the actuators.

Detection of the fault by observers: We are developed residual generation by using a banc of observers , for faults detection and localization , on the direct injection diesel engine. (Abdelkader AKHENAK[8]) we proposed one method of detection and rebuilding of faults sensors by using an neuro-fuzzy observer.

Detection by a banc of observers: In this study we supposed that the state space vector is completely observed and one rebuilds as many outputs as we have measurements. The number of observer is equal to measured outputs number, Fig. 7.

With this intention and after presenting the two F.D.I, we are going to present a limited number of simulations because the article space is limited. It will be possible to show more examples.

SIMULATION OF (LOLIMOT) AND STRUCTURE F.D.I

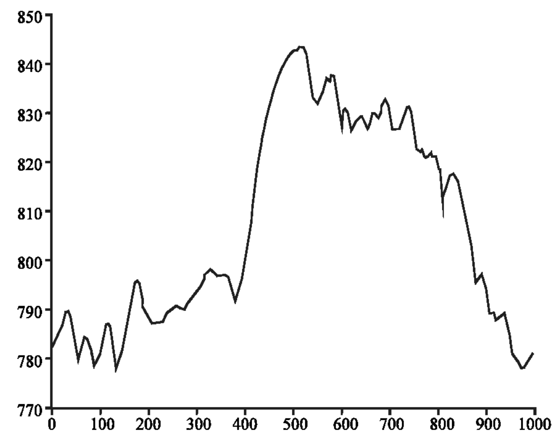

Fig. 7: Variation of the temperature of exhaust manifold training signal

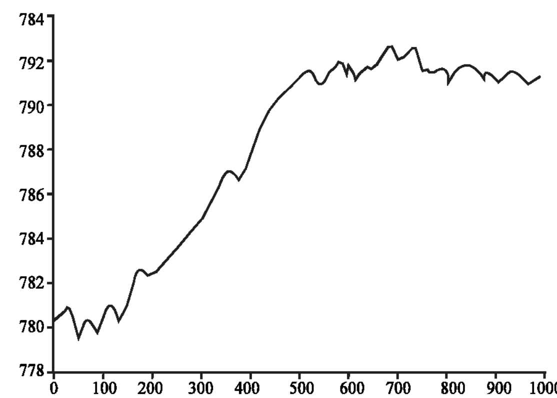

Fig. 8: Variation of the temperature of exhaust manifold validation signal

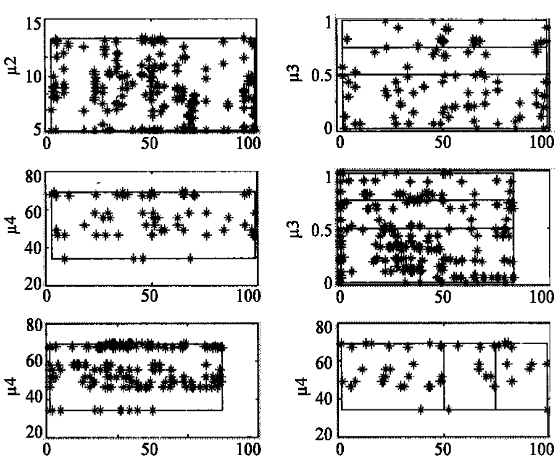

Fig. 9: Partitioning in under space of given function of membership

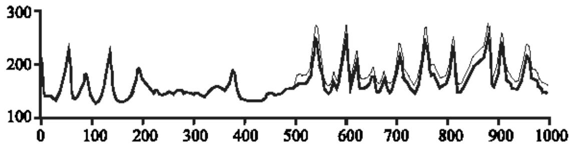

Fig. 10: Change of the signal with a sensor fault

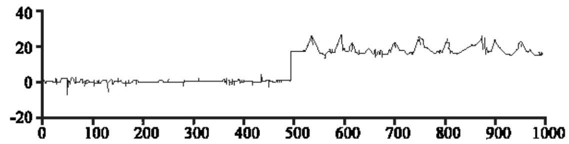

Fig. 11: Residue generated by multi observers of admission pressure

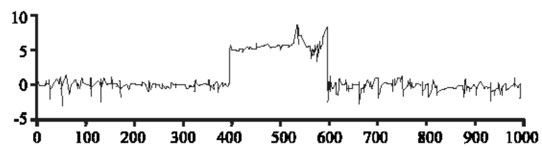

Fig. 12: Residue generated by projection on parity space of admission pressure

The results and the validation of multi model identification by (Lolimot) Fig. 7-9.

The simulation of fault of pressure sensor of admission one considers a fault pressure sensor of admission one derives at instant 500 $_S$ represented on the Fig. 10.

GRAPHIC INTERFACE AND STRUCTURE HUMAN MACHINE*

Graphic interfaces: During the simulation of F.D.I under Matlab, a graphic interface is created allowing visualization of the behaviour of the engine subjected to possible faults.

Human machine structure: In this precise field which is in fact the design of a structure of detection of faults and diagnosis in the diesel engine, the cooperation intervenes between the designer and the conductor on one hand and the embarked computer on the other hand, this cooperation is desired according to the way shown by the diagram of the Fig. 14.

After having implemented an evolutionary structure on the embarked computer the communication through Internet with the designer this will make it possible to make evolve/move the data base, the information displayed, on the management reports will have an impact on the safety of the driving and on a possible intervention of its maintenance[9].

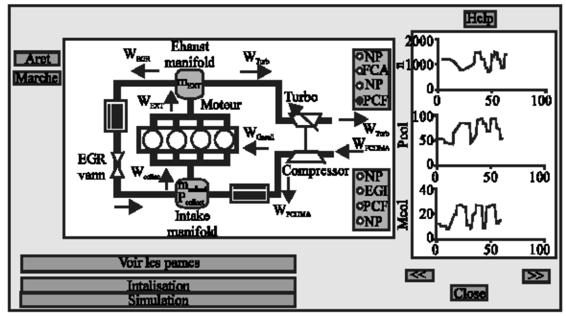

Fig. 13: Graphic interfaces

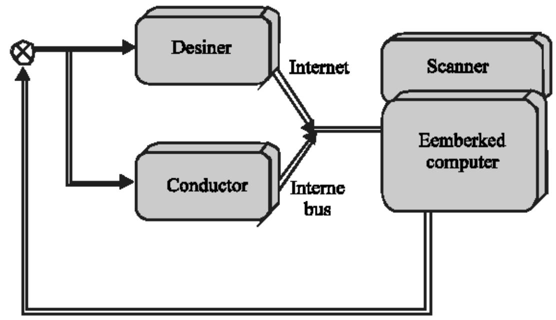

Fig. 14: Structure of human-machine cooperation

The diagnosis of the faults is established in cooperation with the scanner this makes the task of the mechanic easier.

CONCLUSION

After analysis of several examples of simulations one can say that F.D.I structure answers clearly in the presence of faults by giving an analysis on the responsible causes.

Finally from this study it should be stressed the perspectives which remain open on proposing the study of the integration of the additive faults the introduction of specific sensor and to detect the presence of water in the gas oil, the insertion of a fault-tolerant command and to enclose the loop it will be necessary to improve the monitoring by the implementation of the structure above of Homme Machine cooperation described.

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