FAULT DIAGNOSIS WITH BIOGEOGRAPHY- BASED OPTIMIZATION

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Abstract. *For the reliability, safety and efficiency improvement of many technical processes, advanced methods of fault diagnosis have become increasingly important. The aim of this work is to explore the advantages of the new biogeography inspired algorithm for global optimization, i.e. Biogeography- Based Optimization (BBO), for the development of model-based fault diagnosis methods. As a first case of study we have considered simulated data of the Inverted-Pendulum benchmark. The experiments considered noisy data and incipient faults in order to analyze the quality of the diagnosis with Biogeography- Based Optimization, mainly in the topic of robustness, sensitivity and time of diagnosis. The results indicate the feasibility of the approach adopted.*

Keywords: *Biogeography- Based Optimization, Fault diagnosis, Parameter Estimation, Robustness, Sensitivity*

1. INTRODUCTION

Fault diagnosis is the process of detection and isolation of a fault (FDI). Taking into account the severe consequences of faults, many FDI methods have been developed. They should guarantee that faults can be detected and isolated early (sensitivity to faults) while rejecting any false alarm caused by noise, external disturbances or spurious signals (robustness) (Isermann, 2005).

The FDI methods are classified in three general groups: those which do not use a model of the process, those which do use a qualitative model of the process and those that are based on a quantitative model (Venkatasubramanian *et al.*, 2003a,b,c; Angeli and Chatzinikolaou, 2004).

The model-based approaches using the quantitative analytical model allow a deep insight into the process behavior (Isermann, 2005) and can be brought down to a few basic concepts such as: the parity space; observer approach; the fault detection filter approach and the parameter identification or estimation approach. The parameter estimation approach is based on the diagnosis of the faults via estimation of the parameters of the mathematical model (Frank, 1990; Patton *et al.*, 2000; Isermann, 2005).

The limitations of the current FDI methods lead to the necessity of new alternatives development that can deal with an appropriate balance between fault sensitivity and robustness to external disturbances, see (Simani *et al.*, 2002; Simani and Patton, 2008). In the particular case of the parameter estimation based method, there is the additional inconvenient of high the computing time which turns it make almost unfeasible for most online applications (Frank, 1990; Isermann, 1993).

In that sense, the main objective of this work is to explore the advantages of Biogeography- Based Optimization (BBO) for the development of robust and sensible FDI methods via direct faults estimation. The selection of BBO is based on the recent and positive applications of this theory to others benchmarks and real-world problems (Simon, 2008; Gong *et al.*, 2010b). For demonstrating the performace of BBO we have considered as case of study the Inverted-Pendulum System (IPS).

The main contribution of this paper can be summarized as: proposal and analysis of BBO application to FDI via direct faults estimation. As a first approximation it was considered an experiment with simulation data of the inverted pendulum benchmark. The analysis of the viability of the proposal is established based on some criteria such as: robustness, sensitivity and computing time. Also some comments regarding comparisons with others FDI methods based on parameter estimation are put forward.

This work is organized as follows. In the second section the BBO is presented. The third section presents our formulation for the application of BBO to the FDI via fault estimations. Subsequently, the IPS benchmark is introduced. The Results section shows the set of test experiments. Finally, some concluding comments are presented.

2. BIOGEOGRAPHY- BASED OPTIMIZATION (BBO)

BBO is a new biogeography inspired global optimization algorithm (Simon, 2008) that was initially applied to optimization problems with discrete domain, but has already been extended to continuous domain (Gong *et al.*, 2010b), and combined with other evolutionary algorithms such as Differential Evolution (Gong *et al.*, 2010a).

On each iteration BBO works with a set of solutions called ecosystem H^n that is defined as a group on n habitats. Each habitat $H_i \in \mathbb{R}^m$, with $i = 1, 2, ..., n$, is identified with a solution to the optimization problem and it is characterized by a habitat suitability index (HSI) which is proportional to its suitability as residence for biological species. HSI is also proportional to the number of species that contains the habitat. Good solutions will have better HSI than bad solutions.

The dynamic of the ecosystem is shown by means of migratory phenomena which is implemented by means of the Migration operator. Each habitat H_i, with $i = 1, 2, ..., n$, can receive or donate species, and such capability is characterized as proportional to the immigration rate λ_i and the emigration rate μ_i, respectively:

$$\lambda_i = I(1 - \frac{S_i}{S_{max}}) \tag{1}$$

$$\mu_i = E\frac{S_i}{S_{max}} \tag{2}$$

where E and I denote the maximum rate for emigration and immigration, respectively; S_i the number of species of the habitat H_i, and S_{max} the maximum number of especies in the ecosystem.

The values λ and μ also state the probability of each habitat to change its number of species from time t to time $(t + \Delta t)$.

$$\dot{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1} & \text{if } S = 0 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1} & \text{if } 1 \leq S \leq S_{max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} & \text{if } S = S_{max} \end{cases} \tag{3}$$

Each habitat can also suffer due to natural perturbations. This is implemented by means of the mutation operator and the mutation rate m_i for each habitat H_i is computing by:

$$m_i = m_{max}(1 - \frac{P_i}{P_{max}}) \tag{4}$$

where m_{max} denotes the maximum mutation rate.

With the migration operator BBO can share the information between solutions. Additionally, the mutation operator tends to increase the diversity of the population.

The basic pseudocode of BBO is described in Algorithm 1 (Simon, 2008).

Algorithm 1 Algorithm BBO

```
Initialize the BBO parameters: n, m, S_max, I, E, m_max, Δt, iter
Generate the initial habitat H^n randomly
For each habitat map the HSI_i to the number of species S_i, compute λ_i and μ_i, see Eq. (1) and Eq. (2).
for j = 1 to j = iter do
  Migration, see Algorithm 2
  Compute the probability P_i of each habitat H_i, see Eq. (3)
  Mutation, see Algorithm 3
  Update HSI_i, λ_i and μ_i
end for
```

The pseudocode of Migration Operator for BBO is described in Algorithm 2, (Simon, 2008).

Algorithm 2 Migration

```
Select H_i with probability ∝ λ_i
if H_i is selected then
  for j = 1 to j = n do
    Select H_j with probability ∝ μ_j
    if H_i is selected then
      Randomly select a component l, with l = 1, 2, ..., m, from H_j
      Replace H_i(l) with H_j(l)
    end if
  end for
end if
```

The pseudocode of Mutation Operator for BBO is described in Algorithm 3 (Gong *et al.*, 2010b).

Algorithm 3 Mutation

For each habitat H_i compute its mutation rate m_i, see Eq. (4)
for $i = 1$ to $i = n$ **do**
  for $l = 1$ to $l = m$ **do**
    Select $H_i(l)$ with probability $\propto \mu_i$
    if $H_i(l)$ is selected **then**
      Mutate $H_i(l)$ with Gaussian mutation
    end if
  end for
end for

3. BBO APPLIED TO FDI VIA PARAMETER ESTIMATION

Let be

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t), \theta) \quad (5a)$$

$$\mathbf{y}(t) = g(\mathbf{x}(t), \theta) \quad (5b)$$

the process model that represents as close as possible the physical laws which govern the process behavior (Isermann, 2005). The vector of state variables is represented by $\mathbf{x}(t) \in \mathbb{R}^n$. The measurable input signals $\mathbf{u}(t) \in \mathbb{R}^m$ and output signals $\mathbf{y}(t) \in \mathbb{R}^p$ can be directly obtained by the use of physical sensors; $\theta_p \in \mathbb{R}^j$ is the process parameters vector and determines the model parameters vector $\theta = [\theta_p]^t$.

The components of the process parameters vector are identified with the components of physical process coefficients vector $\rho \in \mathbb{R}^k$, and in general $k \neq j$. The variations of these coefficients are generally related with faults. The estimations of the vector θ_p will allow to detect the faults once the relationship between $\theta_p - \rho$ and $\rho-$faults are established (Isermann, 1984). This divides the diagnosis into two steps, the first one considers the estimations of the parameters vector θ_p, permitting the detection; and the second includes the determination of the faults based on the mentioned relationships. If $j \leq k$ the relationship between process parameters and physical coefficients will be not one- one and as consequence some faults will be not separable (Isermann, 1984, 2005).

For estimating θ_p, two main approaches have been considered: minimize the equation error or minimize the output error. The first one permits the use of the least square estimator and it is also necessary the use of the derivatives of the input and output data vector as well the use of filters for improving the numerical properties. In the second case numerical optimization is necessary, and the resulting high computational time brings difficulties in the applications for real on-line processes (Isermann, 2005). Some applications of evolutionary algorithms and neural networks have been reported in that sense (Witczak, 2006; Yang *et al.*, 2007)

In order to avoid the described problem of the FDI based on the parameters estimation we have considered the model that also includes the faults. In this case the model (5a, b) considers that the influence of the faults is absolutely represented by the fault parameters vector $\theta_f \in \mathbb{R}^l$ and $\theta = [\theta_p \ \ \theta_f]^t$. This vector contains the information regarding magnitude of each fault f_l. That is the reason why the estimations of the vector θ_f will allow diagnosing directly the system. This kind of faults modelling has been widely used for other FDI model based methods such as parity space and observer approach (Frank, 1990; Simani *et al.*, 2002; Ding, 2008) but not in the case of the methods based on parameters estimation.

Considering the process parameters vector θ_p to be constant, the estimation of the vector θ_f can be obtained from the solution of the minimization problem

$$\begin{aligned} \min \quad & F(\hat{\theta_f}) = \sum_{t=1}^{N_s} \left[\mathbf{y}_t(\theta_f) - \hat{\mathbf{y}}_t(\hat{\theta_f})\right]^2 \\ \text{s.a} \quad & \theta_{f(min)} \leq \hat{\theta_f} \leq \theta_{f(max)} \end{aligned} \quad (6)$$

where N_s is the number of sampling instants, $\hat{\mathbf{y}}_t(\hat{\theta_f})$ is the estimated vector output at each time instant t, and it is obtained from the model given by Eqs. (5a, b); $\mathbf{y}_t(\theta_f)$ is the output vector measured by the sensors at the same instant t (Isermann, 2005). This procedure is represented in the Fig. 1.

For the solution of the optimization problem that was specified in Eqs. (5a, b), even in a noisy environment and with independency of the linearity or not with respect to the parameters θ_f, bio-inspired algorithms can be applied. In the present work the BBO is implemented.

The idea behind the application of BBO is to perform a robust and sensitive diagnose of the system, via direct fault estimation, with an acceptable computational effort wich makes it feasible for the on-line diagnose and avoiding dividing the diagnosis in two steps as the usual FDI parameter estimation methods require to do.

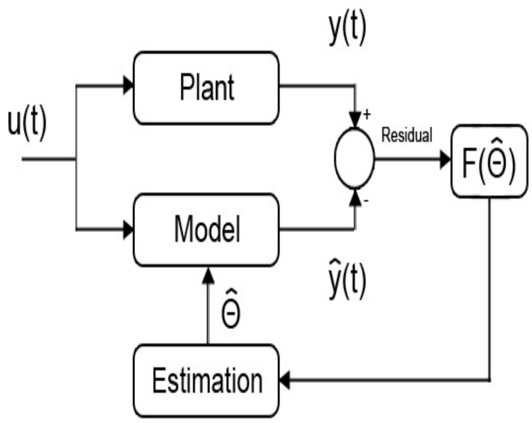

Figure 1. Representation of the FDI based on parameter estimation.

4. STUDY CASE: INVERTED-PENDULUM SYSTEM (IPS)

This system is considered as a benchmark for control and diagnosis. It is formed by an inverted pendulum mounted on a motor-driven car. The objective is to keep the beam perpendicular to the vertical position. Here it has been considered only the two -dimensional problem where the pendulum moves only in the plane of the paper, see Fig.2.

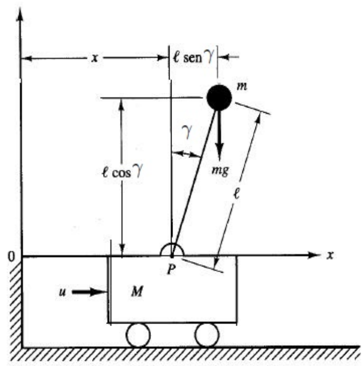

Figure 2. Inverted- Pendulum system

The mathematical model of the IPS has been widely studied, see (Ding, 2008). The system is described by a state-space representation of a linear time invariant system, affected by additive faults:

$$\dot{\mathbf{x}}(t) = A\mathbf{x}(t) + B\mathbf{u}(t) + E_f f(t) \tag{7a}$$

$$\mathbf{y}(t) = C\mathbf{x}(t) + F_f f(t) \tag{7b}$$

The state vector is $\mathbf{x} = [\gamma\ \dot{\gamma}\ x\ \dot{x}]^t$, where γ and $\dot{\gamma}$ are the angle of the pendulum with respect to the vertical position and the angular velocity respectively; x and $\dot{x}$ are the position and the velocity of the car respectively. The outputs of the system are $\mathbf{y} = [\gamma\ x]^t$ and the input $\mathbf{u}(t) = F$ is the control force applied to the car. The relationship between each element of the fault vector $f(t) = [f_1\ f_2\ f_3]^t$ and the faults of the system is one to one: f_1 causes undesired movement of the car taking place in the actuator, this kind of fault is represented by an additive fault affecting the system input F; f_2 represents a fault in the sensor of γ and f_3 identifies faults in the sensor that measures x. The matrices $A,\ B,\ C,\ E_d,\ F_f$ are known and with appropiate dimensions:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \frac{m+M}{Ml}g & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ -\frac{m}{M}g & 0 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ -\frac{1}{Ml} \\ 0 \\ -\frac{1}{M} \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad E_f = [B0] \quad F_f = [0I_{2x2}]$$

Considering the system with the characteristics $M = 2$ kg, $m = 0.1$ kg and $l = 0.5$ m, the following matrices are obtained:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 20.601 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ -0.4905 & 0 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ -1 \\ 0 \\ 0.5 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad E_f = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \\ 0.5 & 0 & 0 \end{bmatrix} \quad F_f = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Let be $\theta_f = f(t)$, and considering the nature of the faults and the properties of the IPS, then the elements of θ_f have the following restrictions:

$$\begin{array}{lll} \theta_{f1} \in \mathbb{R}: & -1 \leq \theta_{f1} \leq 1 & \text{N} \\ \theta_{f2} \in \mathbb{R}: & 0 \leq \theta_{f2} \leq 0.01 & \text{rad} \\ \theta_{f3} \in \mathbb{R}: & 0 \leq \theta_{f3} \leq 0.02 & \text{m} \end{array} \tag{8}$$

In order to make a direct diagnosis of the system we can achieve estimations of $\theta_f = f(t)$. In that sense the inverse problem of FDI that was formulated in Eq. (6) should be solved.

4.1 Data simulation

The behavior of the system was simulated under no faults and under different faulty situations. The direct problem given by Eqs. (7a, b), was numerically solved with the fourth order Runge Kutta method. In Figs. 3 and 4 are shown two different situations that were simulated.

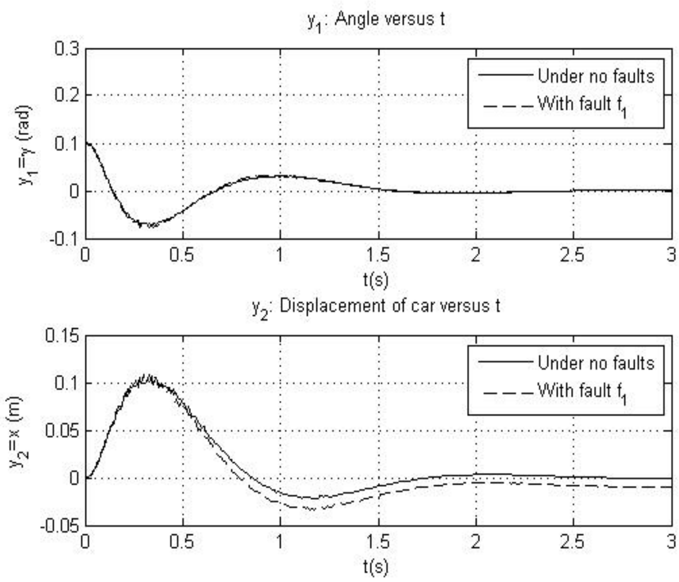

Figure 3. Simulation with no faults and fault f_1, corrupted with 5 % level noise

5. RESULTS

With the aim to analize the merit of our proposal, direct diagnosis via estimations of the faults of the systems based on the output error with BBO, three aspects have been considered: robustness, sensitivity and computing time. With this goal in mind the IPS is diagnosed under the faulty cases exposed in Table 1.

Table 1. Faulty situations to be diagnosed in the IPS

	Case 1	Case 2	Case 3
f_1	0	0.5	-0.5
f_2	0.01	0.01	0
f_3	0.02	0.02	0.004

In order to diagnose the faults, the minimization problem formulated in Eq. (6) was implemented considering BBO. All the implementations were based on the Algorithms 1-3 with MATLAB R2008a. The stopping criterion was the number

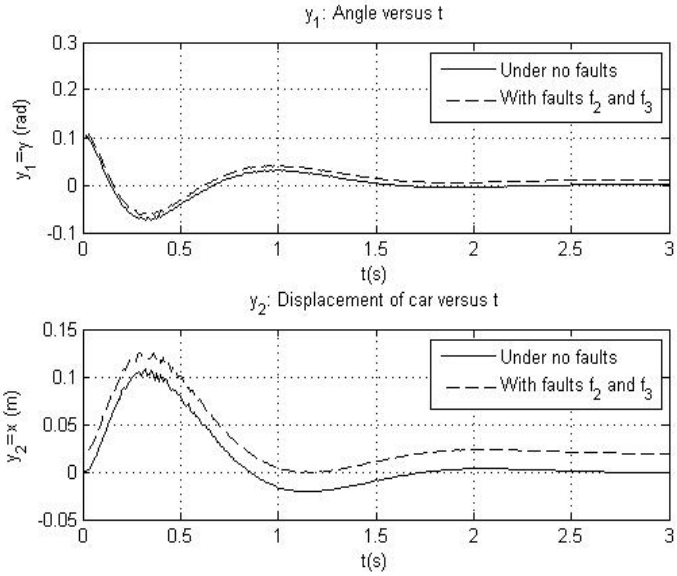

Figure 4. Simulation with no faults and faults f_2 and f_3, corrupted with 5 % level noise

of iterations $iter = 100$. The parameters of BBO were $n = 30$, $m = 2$, $S_{max} = 30$, $I = 1$, $E = 1$, $m_{max} = 0.05$ and $\Delta t = 0.1$.

The number of repetitions was 30 in each case and two descriptive statistics were computed: arithmetic average and variance. The abbreviations that were used in the tables are $\bar{\theta}_f$ and $\sigma_{\hat{\theta}_f}$ for the arithmetic average and the variance, respectively, of the estimations of the faulty parameters and $\bar{t}$ for the arithmetic average of the computing time, in seconds. It has been also computed the relationship $[\sigma_{\hat{\theta}_{fi}}/\bar{\theta}_{fi}] \times 100$ for each fault. All cases considered data with 5 % of noise in order to simulate the effect of disturbances.

In Table 2 are shown the results of the diagnosis for the proposed faulty situations of Table 1. The worst result is observed in the estimation of the fault f_1 which represents a fault in the actuator. For the second case the fault f_1 is detected but the estimation of the magnitude of the fault is a half of the real value. The best estimation of the actuador fault was in the Case 3 which is characterized by no fault in sensor 1 and a small fault in sensor 2. The other two cases that considered maximum values of faults for both sensors did not make a correct diagnose of the actuator fault. In all cases the sensors faults were well diagnosed. The BBO permit robust and sensitive diagnose for sensor faults but for the case of actuator faults did not give the same results. The preliminary results indicate that the presence and magnitude of the actuator fault did not affect the diagnose of the sensor faults. On the other hand the diagnose of actuador fault seems to be affected by the presense of sensors faults. In that sense other experiments have been considered and they are presented in the Table 3.

Table 2. Diagnosis obtained in faulty situations of the Table 1: data with 5 % of noise

	Case 1	Case 2	Case 3
$\bar{\theta}_f$	[0.0468; 0.0095; 0.0180]	[0.2450; 0.0095; 0.0181]	[-0.623; 0.0005; 0.0030]
$\sigma_{\hat{\theta}_f}$	[6.0e-003; 6.2e-008; 4.6e-007]	[4.0e-002; 8.3e-008; 1.5e-006]	[4.6e-003; 1.0e-007; 2.5e-007]
$\frac{\sigma_{\hat{\theta}_{fi}}}{\bar{\theta}_{fi}} \cdot 100$	[12.8205; 0.0007; 0.0026]	[16.3265; 0.0009; 0.0083]	[0.7384; 0.0200; 0.0083]
$\bar{t}$	75.3367	75.3481	75.066

In Table 3 are shown the new faulty situations that are introduced. The Case 4 presents only an actuator fault. The Case 5 and the Case 6 also introduce fault in the sensor of γ and x respectively.

The results of the application of BBO to the situations of Table 3 are shown in Table 4. Initially the data were kept corrupted with 5 % level noise. The results indicate that the actuator fault can be correctly diagnosed with BBO when no sensor faults are presented (Case 4). In the other two cases the diagnosis of the actuator fault is incorrect with the worst result in Case 6 that contains fault in the sensor of x. In all the cases the diagnosis of the sensor faults is correct. The computing time is quite similar for the different cases, despite the number of faults affecting the system.

In order to analyze the performance of BBO with respect to robustness and sensibility, some experiments with the faulty situations of Table 3 are considered. This time the data is corrupted with 10 % level noise in order to simulate

Table 3. Faulty situations to be diagnosed in the IPS

	Case 4	Case 5	Case 6
f_1	0.1	0.1	0.1
f_2	0	0.01	0
f_3	0	0	0.02

Table 4. Diagnosis obtained in faulty situations of the Table 3: data with 5 $\%$ of noise

	Case 4	Case 5	Case 6
θ_f	[0.1170; 0.0008; 0.0002]	[0.2197; 0.0094; 0.0004]	[-0.0542; 0.0004; 0.0188]
$\sigma_{\hat{\theta}_f}$	[1.7e-003; 1.8e-008; 7.3e-007]	[2.6e-003; 2.1e-008; 1.9e-008]	[8.6e-003; 3.0e-008; 1.4e-008]
$\frac{\sigma_{\hat{\theta}_{fi}}}{\theta_{fi}} \cdot 100$	[1.4530; 0.0022; 0.3650]	[1.1834; 0.0002; 0.0047]	[-15.8672; 0.0075; 0.0001]
$\bar{t}$	74.6885	74.8486	74.7741

disturbances that can affect the correct diagnosis. The results are shown in Table 5 and comparing with the results on Table 4, it can be concluded that the performance of BBO is quite similar independently the level of noise contains in data. In all the cases the diagnosis of the sensors faults was robust and sensitive. The computing time is similar in the different levels of noise.

Table 5. Diagnosis obtained in faulty situations of the Table 3: data with 10 $\%$ of noise

	Case 4	Case 5	Case 6
θ_f	[0.1974; 0.0012; 0.0004]	[0.2840; 0.0081; 0.0002]	[-0.8459; 0.0003; 0.0138]
$\sigma_{\hat{\theta}_f}$	[1.6e-003; 3.0e-007; 4.1e-007]	[3.0e-003; 7.2e-007; 5.5e-007]	[2.7e-004; 1.0e-008; 1.0e-006]
$\frac{\sigma_{\hat{\theta}_{fi}}}{\theta_{fi}} \cdot 100$	[0.8105; 0.0250; 0.1025]	[1.0563; 0.0089; 0.2750]	[-0.0319; 0.0033; 0.0072]
$\bar{t}$	74.5261	74.5799	74.6200

In Table 6 are shown the results of diagnosis of the cases on the Table 3, but the number of iterations was reduced to 50. The noise is kept on 10%. The quality of the estimations is quite similar to the ones obtained with 100 iterations, but now the computing time was reduced on the half.

Table 6. Diagnosis obtained in faulty situations of the Table 3: noise of 10% and 50 iterations

	Case 4	Case 5	Case 6
θ_f	[0.1373; 0.0006; 0.0004]	[0.2130; 0.0094; 0.0004]	[-0.1013; 0.0004; 0.0185]
$\sigma_{\hat{\theta}_f}$	[5.2e-003; 7.4e-007; 1.0e-007]	[1.5e-003; 1.0e-008; 1.0e-008]	[1.2e-002; 9.0e-007; 1.2e-007]
$\frac{\sigma_{\hat{\theta}_{fi}}}{\theta_{fi}} \cdot 100$	[3.7873; 0.1233; 0.0250]	[0.7042; 0.0001; 0.0025]	[-11.8460; 0.2250; 0.0006]
$\bar{t}$	37.3246	37.5328	37.3398

6. CONCLUSIONS

This study indicates first that the use of mathematical models that represent directly the influence and magnitude of the additive faults affecting the system are viable for the diagnosing of the system via faults estimation while avoiding the division of the diagnosis into two steps which generally requires use of several techniques. As a second contribution this study shows that the application of BBO is perfectly feasible for the development of fault diagnosis methods based on faults estimation. The principal advantages are the easy generalization to other systems, the robustness, sensitivity and that the computing time makes possible the on- line diagnose.

The poor results observed in the diagnosis of the actuator faults in presence of sensor faults are associated to the structure of the problem considered and not with any limitation of BBO.

It is our interest to analyze the influence of the different parameters of BBO in the improvement of its behavior for the FDI problem, basically in the area of robustness, sensitivity and computing time as well its hybridization with other evolutionary algorithms.

It is also our concern to extend the proposed approach for multiplicative faults.

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