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A DC Motor Fault Detection, Isolation and Identification Based on A New Architecture Artificial Neural Network

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Abstract— **Any diagnosis procedure should be rapid and efficiency. In the presence of the noise and unknown inputs, the diagnosis procedure could generate false alarms. This paper focuses in the fault detection, isolation and identification when a fault affected the sensors of a DC motor worked in disturbance environment. The chosen technique should take account the two issues: the noise and the unknown inputs. As a solution the Artificial Neural Network is adopted in order to generate a robust residuals and therefore to minimize the false alarms. A new ANN architecture is proposed to achieve this purpose. The simulation results proved the rapidity and the efficiency of the proposed procedure.**

I. INTRODUCTION

It is necessary that electrical equipment achieve the desired operating mode. For this reason, it should be controlled at each time. Unfortunately, the equipments performance degrades after a failure occurrence. In that case, the early diagnosis allows one to plan the required maintenance actions and decreases the number of emergency shutdowns of any operating process.

The Fault Detection, Isolation and Identification (FDII) could be achieved using varied approaches and techniques. Each one of them has advantages and disadvantage [2]. Analytical approaches such as parity space approach are based on analytical model [3].This approach is based on residuals evaluations which are generated from the parity equation [4]-[5]. The residuals are theoretically nulls, if the system is in normal operation, but are large, if the system is affected by faults. The developed models are based on physics theories which are not usually available and are made under assumptions. Therefore, there are lacks of precisions because the noise and the unknown inputs.

In order to fulfill fault detection, isolation and identification under the disturbance and the unknown inputs, several methods could be used. These methods should satisfy the fault rapidity and accuracy. In this paper, an intelligent technique is adopted. The Artificial Neural Network ANN is chosen as a solution to the problem of diagnosis. Many researched work are interesting to the ANN as an excellent technique for the FDII. Two ANN models: dynamic neural model (DNM) and the time delay neural network (TDNN) are used in [6]. They are investigated in order to design and develop an FDI scheme for aircraft gas turbine engines. A nuclear process is a complex system which is equipped with many sensors. In this context, any incorrect measurement could cause damage in the process. Therefore, a sensor fault should be detected and isolated. A new method based on the capabilities of the ANNs is developed in [7]. In [8], an unsupervised ANN based on Adaptive Resonance Theory (ART) is tested for FDI on an automated O-ring assembly machine testbed. The performance and practicality of the proposed technique are compared to those of the conventional rule-based method. The obtained results show that the fault detection was achieved using ART ANN using minimal modeling requirements. A multilayered approach of the high-order neural network is proposed in [9]. It used to develop a robust fault detection scheme. Comparing to multi-layer perceptron neural network, these networks can approximate any function with less parameters. Such propriety makes the proposed network useful to generate a residual for FDI of dynamic system. The inter-turn short circuit in stator windings of a Permanent magnet synchronous motor (PMSM) fault is studied in [10]. A multilayer artificial neural network (MANN) has been proposed in order to diagnosis and to classify the different levels of short circuit. A novel fault diagnostic technique based on ANN is applied to photovoltaic systems [11]. The work has been validated with experimental setup.

Electric motors are so much a part of everyday life. They are used in many vital applications such as transportation, vehicle, computer, industry…[1]. There are many electrical motors types: the DC current motor, induction motor… As any system, they should be controlled but when a fault affected the sensors, the orders of the controlled operation become incorrect. So, the DC motor is likely to faulty operation or breakdown. And in many cases, they could cause a dreadful damage. In order to avoid these drawbacks and to guarantee the continuity of the operating mode, the Fault Detection Isolation and Identification (FDII) becomes necessary.

In the rest of this article, the second section is dedicated to DC motor modeling. The third section describes the FDII procedure. The obtained results are illustrated and discussed in the fourth section. Finally the section five concludes the work.

II. SYSTEM MODELING

DC motor can be described by the ordinary differential equations.

$$\frac{di_a(t)}{dt} = -\frac{R}{L} i_a(t) - \frac{K}{L}\omega(t) + \frac{u_a(t)}{L} \quad (1)$$

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$$\frac{d\omega(t)}{dt} = \frac{K}{J} i_a(t) - \frac{f}{J}\omega(t) \quad (2)$$

Where $i_a(t)$ is the armature current, $\omega(t)$ is the shaft speed, $u_a(t)$ is the input voltage, R and L are the armature resistance and inductance respectively, K *is* the speed and torque proportionality constants, J is the moment of the inertia and f is the viscous damping constant. All the parameters are given in the table.

Table.1 Parameters values

Parameter	value
R	8 Ω
L	0.129mH
f	0.0218 N.s/m
j	0.02 kgm^2
K	0.7745

The discrete state space equation derived from (1) and (2) is

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k) = Cx(k) \end{cases} \quad (3)$$

Where, $x(k)$ are the system states, $u(k)$ is system input and $y(k)$ are the system outputs.

- A represents the internal interconnection among state variables,
- B represents the input-to-state direct connection,
- C represents the state-to-output direct connection.

Where $$x(k) = \begin{bmatrix} i_a(k) & \omega(k) \end{bmatrix}^T \quad (5)$$

$$u(k) = u_a(k) \quad (6)$$

$$A = \begin{bmatrix} 0.9380 & -0.0060 \\ 0.0387 & 0.9989 \end{bmatrix} \quad (7)$$

$$B = \begin{bmatrix} 0.0078 \\ 0 \end{bmatrix} \quad (8)$$

And $$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (9)$$

The state space description should take into account the disturbance and the unknown inputs so it could be equal to:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + Gd_1(k) \\ y(k) = Cx(k) + Ff(k) + Dd_2(k) \end{cases} \quad (4)$$

Where

- G represents the unknown and the noise inputs among the input-to-state direct connection $u(k)$,
- F represents the matrix sensors faults,
- D represents the unknown and the noise input-to-output direct connection or input/output coupling,
- $d_1(k)$ are the noise and unknown inputs associated to the inputs,
- $d_2(k)$ are the noise and unknown inputs associated to the outputs,
- $f(k)$ are the sensors faults associated to the outputs.

Sensors bias is the main types of faults. The white Gaussian noise is added to the voltage input $u(k)$. A fault type bias equal to 3 and 20 are added respectively to current and speed sensors. Therefore, $f(k)$ is equal to $\begin{bmatrix} 5 \\ 20 \end{bmatrix}$

$$G = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \; D = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

There are different possibilities of the *F*. It could be equal to:

-[0 1] when the fault occurred in speed sensor,

-[1 0] when the fault occurred in current sensor,

-[1 1]when the fault occurred in speed and current sensors.

There are different scenarios should take be account:

-Only speed sensor fault,

-Only current sensor fault,

-Speed and current sensor faults.

In this paper the objective is firstly to detect and to estimate the amplitude of the fault, and secondly is to isolate the fault

III. FAULT DETECTION, ISOLATION AND ESTIMATION BASED ON ARTIFICIAL NEURAL NETWORK

A. *FDII procedure*

The proposed procedure is based on artificial neural network in order to take account the error modeling, the noise and the unknown inputs. As illustrated in Fig.1. the procedure is divided into two steps; the first is the detection and identification fault, the second is the isolation step.

B. Detection and fault amplitude estimation step

This step aims firstly to detect the occurrence of the fault and secondly to determine the fault amplitude.

The detection step composed of a two artificial neural networks. The first has two inputs which are the measurements of the current and the voltage control, and one output $r_1(k)$ which is the first residual. The second has also two inputs: the measurements of the speed and the voltage control. As the first one the second neural network has one output $r_2(k)$. Hence, each neural network is sensible to one sensor, but the two neural networks are sensible to the actuator. As shown in Fig.2. both the two neural networks are composed of three layers: two hidden layers and one output layer.

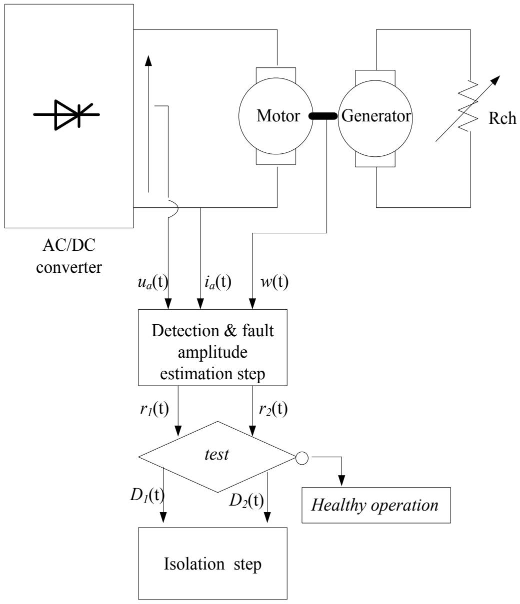

Figure 1. FDII procedure.

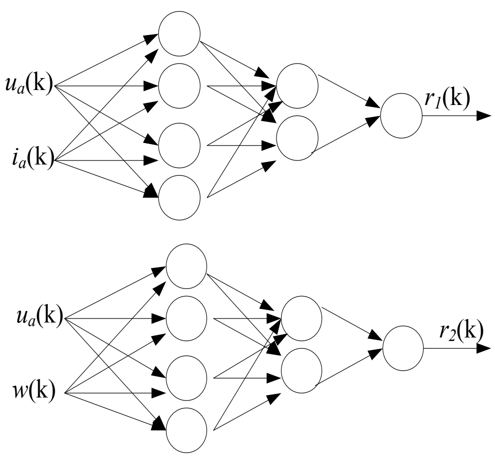

Figure 2. The two artificial neural networks used for detection and amplitude fault estimation step.

The learning procedure is done with a rich database chosen in order to take account the maximum of operating point. The Fig.3. shows the database of the voltage control *u(k)*. The Fig.4. and Fig.5. illustrate respectively the corresponding current and speed sensors measurements. The considered sensor fault is a bias fault equal to 5 for the current sensor and equal to 20 for the speed sensor. The two residuals should be constructed to be null in case of healthy operation. In case of the current sensor fault the first residual $r_1(k)$ is equal to 5 and the second residual $r_2(k)$ is equal to 0. In case of speed sensor fault, the two residuals are equal respectively to 0 and 20. The Fig.6. and Fig.7. show the databases used in ANN learning procedure dedicated to the two residuals $r_1(k)$ and $r_2(k)$.

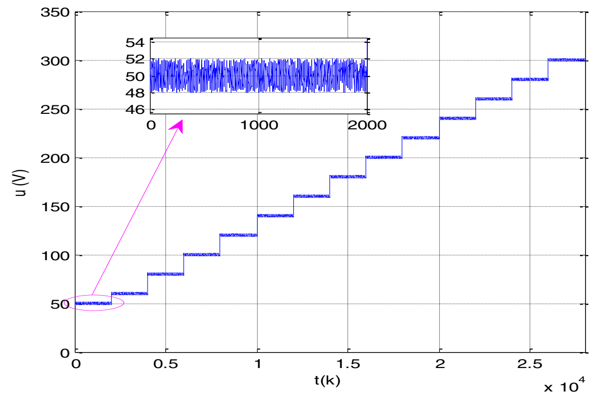

Figure 3. The voltage control database.

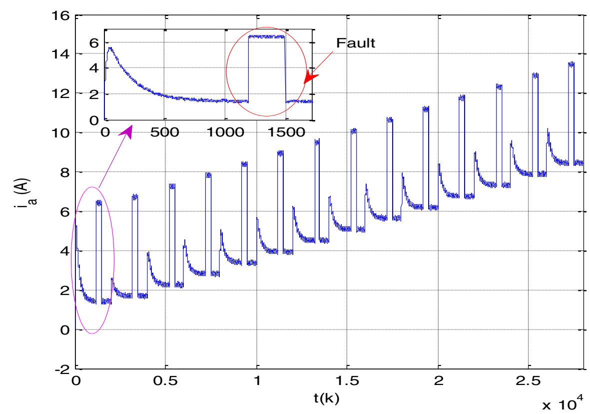

Figure 4. Sensor current database.

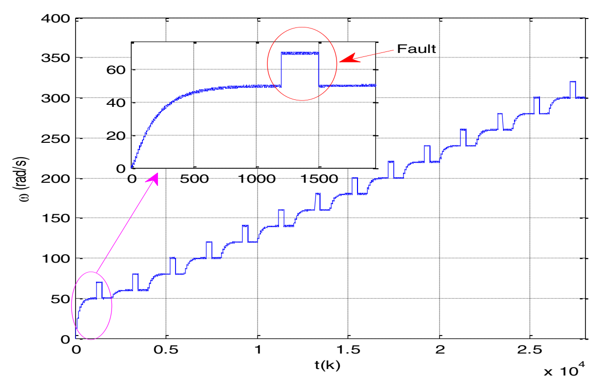

Figure 5. Sensor speed database.

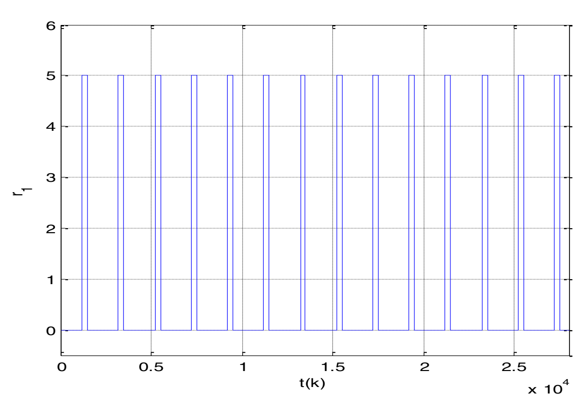

Figure 6. Residuals database.

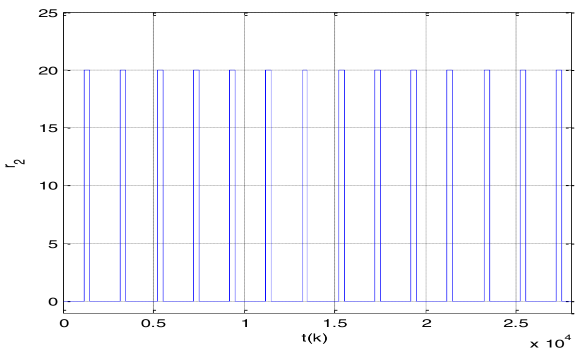

Figure 7. Residuals database.

The simulation results are obtained using Neural Network Toolbox in Simulink Matlab ©. The two ANNs are composed of 4 layers: input, output layer and two hidden layers. The first hidden layer composed of 4 neurons for the second hidden layer there are two neurons. Except the output neuron, all the neurons are activated using tansig function. The Levenberg Marquardt algorithm is chosen for the learning procedure. The Fig.8. illustrates the graphical interface of the artificial neural network. The Fig.9. shows the learning error. It attends $1.5936.10^{-14}$at epoch 22.

C.Isolation fault step

This step aims to isolates the sensors faults location. The objective consists in determining which sensor is in dysfunction operation mode. The two residuals r_1 and r_2 are compared to a threshold. The test results are a decision signal F_1 and F_2. For a robust isolation step, the structural indicators are chosen. Therefore, $F_1$and F_2 equal to 0 if the two residuals remain in the threshold band. Otherwise, they deviate to 1. If the indicator is null, the operating mode is healthy. And if it equal to 1, the operating mode is dysfunction. The Fig.10. illustrates the residuals evaluation tests. The Table.2. illustrates the signature table used for the isolation step.

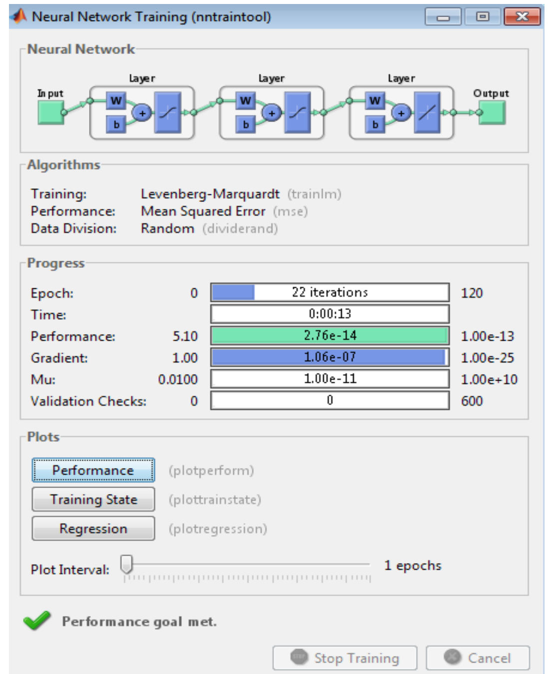

Figure 8. Learning graphical interface.

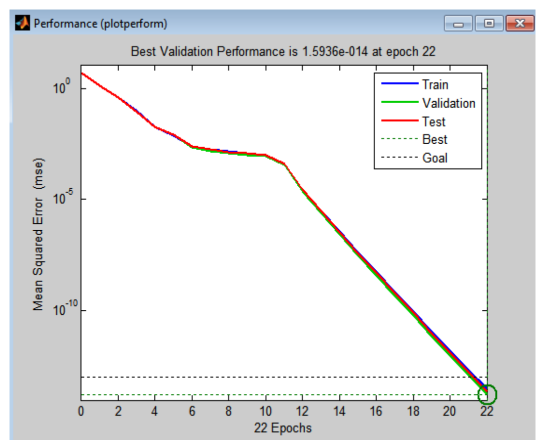

Figure 9. Learning error evolution.

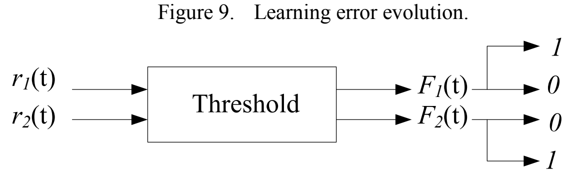

Figure 10. Residuals evaluation step.

TABLE I. SIGNATURE TABLE FOR ISOLATION STEP.

Fault location / Indicators	**Healthy operation**	**Only speed sensor**	**Only current sensor**	**Speed and current sensors**
F_1	0	0	1	1
F_2	0	1	0	1

IV. RESULTS AND DISCUSSION

To evaluate the proposed procedure, the healthy operating mode and the faulty one are tested.

A. Healthy operation

In the case of healthy operation, the two residuals (Fig.10., Fig.11.) are approximately nulls. They don't exceed respectively 10.10^{-6} for r_1 and 20.10^{-5} for r_2. Therefore, they remain in the threshold range equal to [-0.1, 0.1]. As a consequence, the two indicators F_1 and F_2 are nulls. The vector $[F_1\ F_2]$ become equal to [0 0]. Comparing to the signature table, the mode operating is healthy.

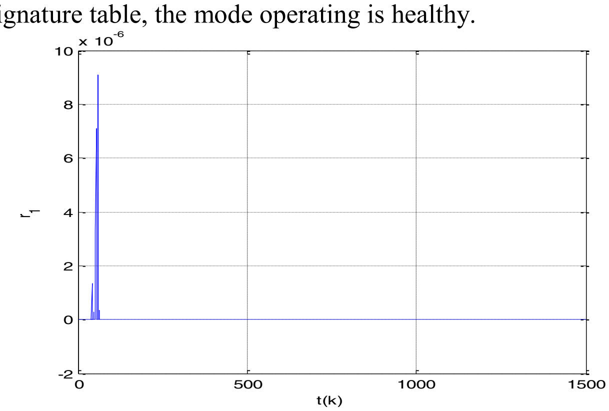

Figure 11. First residual r_1 evolution in case of healthy operation.

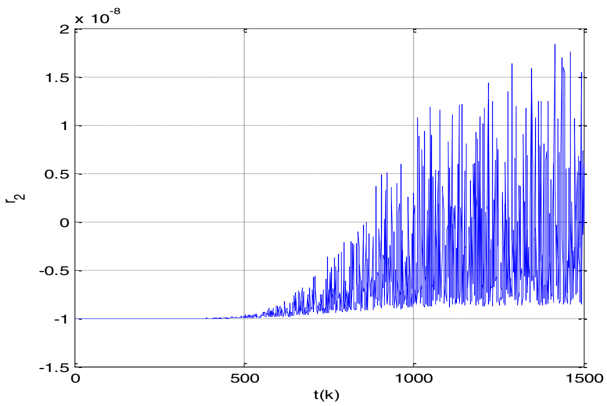

Figure 12. Second residual evolution in case of healthy operation.

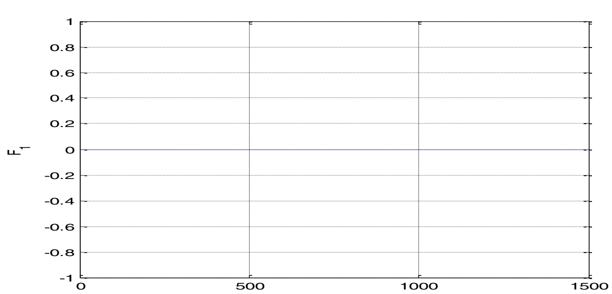

Figure 13. First indicator F1 evolution in case of healthy operation.

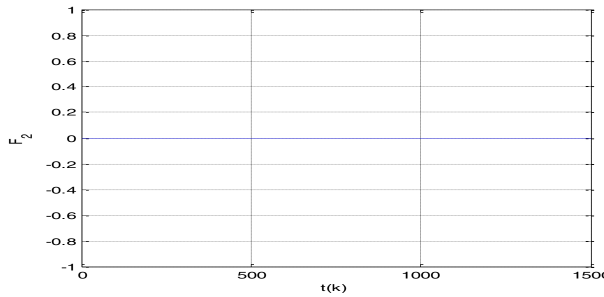

Figure 14. Second indicator F2 evolution in case of healthy operation.

B. Speed and current sensors faults

To evaluate the faulty case, whether it is current sensor fault or speed sensor fault, an intermittent faults are injected in different instants. As shown in Fug.15. and Fig.16. the faults appears at t_{d1} and t_{d2} in case of current sensor and at t_{d3}, t_{d4} and t_{d5} in case of speed sensor. Until t_{d3}, the mode operating is healthy. At t_{d3}, the residual r_1 is equal to 0, but the residual r_2 is set to 20, as it illustrates in Fig.17. and Fig.18. Hence, $[r_1\ r_2]$ is equal to [0 20]. As sequence, the vector $[F_1\ F_2]$ begins equal to [0 1]. According to the signature table, it consists in speed sensor fault. At t_{d1}, a fault type bias occurred on current sensor, so the residuals r_1 becomes equal to 5 and as a sequence the fault indicator F_1 sets to 1. The vector $[F_1\ F_2]$ deviates to [1 1]. It becomes a current and speed faults.

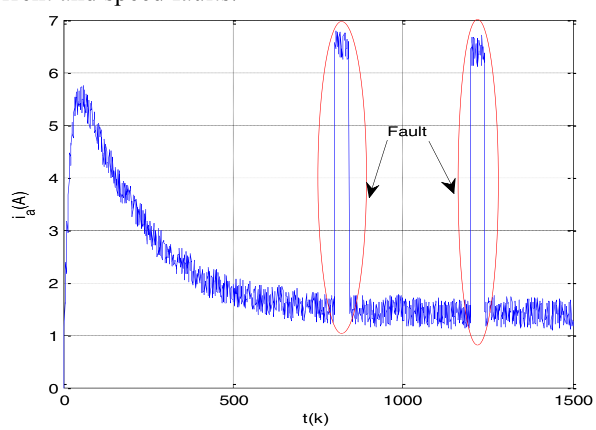

Figure 15. Current sensor measurements.

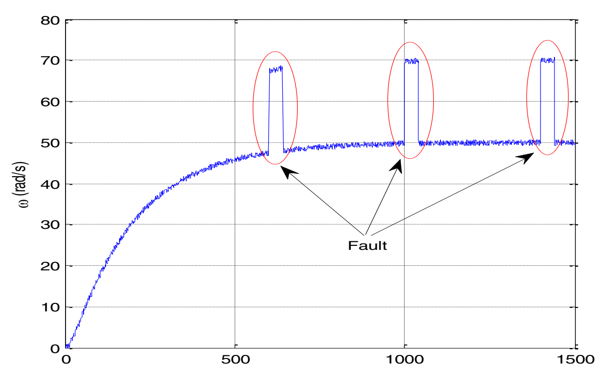

Figure 16. Speed sensor measurements.

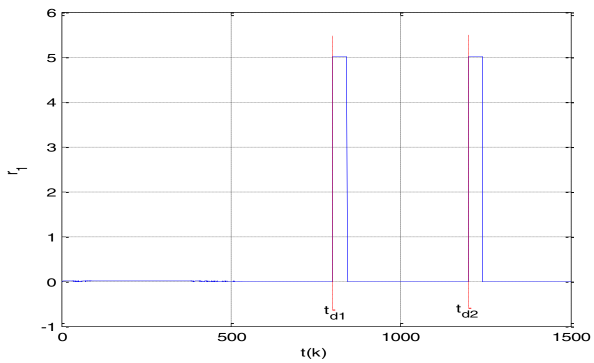

Figure 17. First residual evolution.

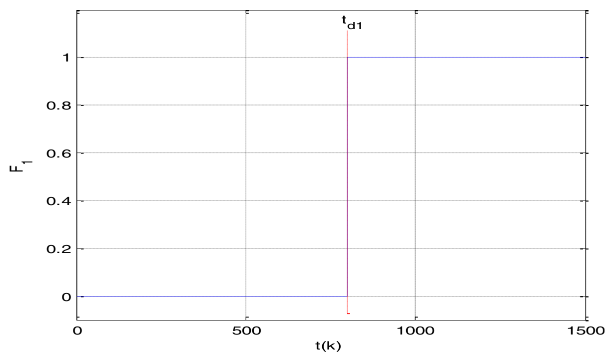

Figure 18. First indicator evolution.

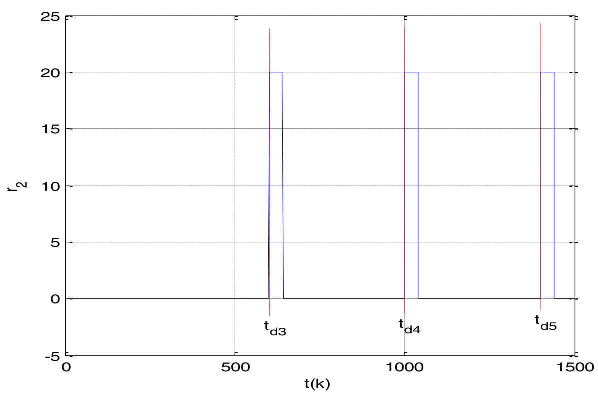

Figure 19. Second residual evolution.

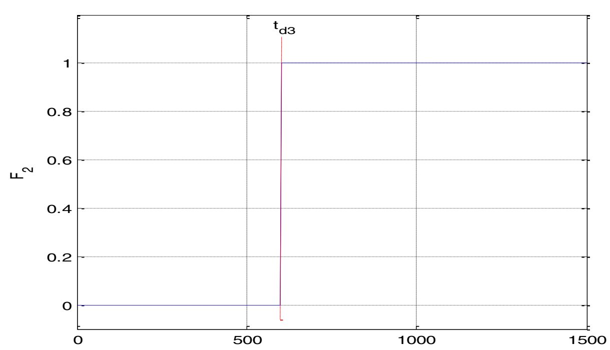

Figure 20. Second indicator evolution.

V. CONCLUSION

In this research work, a robust FDII of sensors fault is presented. The proposed algorithm proves a rapidity and robustness against the disturbance, the noise and the unknown inputs. The ANN proves immunity to the false alarms. It allows the fault detection, isolation and identification. After this step, a fault tolerant control is suggested in order to prevent the system breakdown and guarantee the continuity of the mode operation.

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