A NEW FAULT DETECTION AND ISOLATION ALGORITHM APPLIED TO DC MOTOR PARAMETERS SUPERVISION

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Abstract. *This paper presents a fault detection and isolation algorithm applied to the monitoring of DC Motor parameters. Fault Detection and Isolation (FDI) schemes are implemented as real-time algorithms whose inputs are plant output observations. They are basically used for a) fault detection: to decide whether the plant is in a normal operating condition or in a faulty one and b) fault isolation: to point out and identify the kind of the fault (if present) among a given fault set. DC Motors suffer from diverse possible critical failures that could compromise its performance and cause severe gear damage, such as, armor coil opening, field coil opening, armature static converter short circuit, field static converter short circuit, armature coil short circuit, field coil short circuit, cooling system failure, lack of bearings and bushing lubrication, armature current sensor failure, field current sensor failure, speed sensor failure. The proposed algorithm uses the singular values of a Hankel matrix built from output measurements to detect and isolate DC Motor parameter failures. The main feature of the proposed algorithm is that it does not rely on the plant model identification. Having obtained a nominal plant image through the singular values of the Hankel matrix, this image can be used to determine, by comparison, any value drift of the plant parameters. Two functional levels of the procedure are distinguished, namely alarm generation and alarm interpretation. At the alarm generation level (detection), the algorithm naturally displays plant failure through the change of the singular values structure and values and at the alarm interpretation level (isolation), the algorithm delivers an image of the plant parameters through the singular values allowing the identification of the faulty parameter. Simulation examples are presented to illustrate the performance of the proposed algorithm.*

Keywords: *Fault detection and isolation; DC motor supervision.*

1. INTRODUCTION

The development of safer and more reliable control systems has been an increasingly need in the last decades. To full-fill the modern standards, the control systems design must include fault detection and isolation issues at their very early design stage. The ultimate goal of these systems is to reach a fault-tolerant control (FTC) environment. Fault Detection and Isolation (FDI) schemes are implemented as real-time algorithms whose inputs are plant output observations. They are used for a) fault detection: to decide whether the plant is in a normal operating condition or in a faulty one and b) fault isolation: to point out and identify the kind of the fault (if present) among a given fault set. Following the FDI diagnosis, on-line procedures are usually needed for FTC purpose, while off-line procedures could be used for maintenance purpose. During the last decades, the international scientific community has presented several fine works. Two main streams can be identified, modeling related techniques (Patton, Frank and Clark, 1989) and artificial intelligence based methods. System theory, signal processing or artificial intelligence approaches have been extensively used according to the available data format. Most of the model-based (Delmaire and Cassar, 1995), (Dvorak and Kuipers, 1989), (Frank, 1993), (Hamsher, Console and De Kleer, 1991), (Iserman, 1984), (Zhang, 1996) and also the non-model-based techniques have been developed based on the comparison of the data produced by the real-time plant operation with some previously obtained knowledge of the system.

This paper presents a novel FDI algorithm based on the singular value decomposition of a Hankel matrix built from plant output measurements. The main feature of the proposed algorithm is that it does not rely on the plant model identification. All it is required is a plant signature that can be experimentally obtained. The paper is organized as follows: Section 2 includes some comments on the FDI problem; Section 3 presents the basic formulation of the Eigensystem Realization Algorithm (ERA); Section 4 is concerned with the singular values based fault detection and isolation (SVFDI) algorithm; Section 5 explores the SVFDI algorithm features through experimental results; Section 6 shows the procedure to obtain the FDI "flags"; and finally, Section 7 presents final comments and conclusions.

2. SOME COMMENTS ON THE FDI PROBLEM

In general, Fault Detection and Isolation (FDI) algorithms use the plant input-output measurements to implement a two-steps procedure: the fault detection and the isolation tasks. The first step is the fault detection step or alarm generation. The problem of the alarm generation is to decide whether the system is in a normal operating condition or not. The set of output measurements along with a previously obtained knowledge of the system constitute the algorithm inputs while a set of generated alarms are the algorithm outputs. The second step consists on the alarms interpretation. The main issue in this case is to correctly decide which faults are present (fault isolation) chosen from a pre-defined fault set. It is also of one's interest to establish their characteristics such as occurrence time, fault size, class, consequences, etc. The input is the set of alarms and the output is the faults isolation, characterization and diagnosis. In the case of FTC, further analysis is usually required to determine whether the system is still capable to perform properly after the failure. The algorithm performance is an important issue that must be always considered. The decisions taken at every step of the FDI problem solution might include and accumulate evaluation errors. The measured variables may include noise and load perturbations that might obscure system failures. Also the knowledge one has about the system nominal operation might include uncertainties. Detection errors and false alarms can be confirmed by their probability of occurrence. Incomplete isolation and false isolation errors can be evaluated by comparison based on the faulty events probability of occurrence.

3. THE ERA ALGORITHM – A VERY SHORT REVIEW

This section reviews the basic formulation of the Eigensystem Realization Algorithm (ERA). The ERA algorithm, as originally proposed by Juang and Pappa (1985)(1986), takes the plant impulse response and builds a Hankel matrix from it, they show that through a matrix factorization a state space realization of the plant can be obtained. Since then, the scientific community has proposed several modifications and improvements mainly applying the technique to model reduction problems (Mitchell, Huston and Irwin, 1990). The ERA algorithm is a very reliable computational procedure originally proposed as a tool for modeling of dynamic linear systems, in this case, the ERA procedure delivers an exact model from the plant noise-free impulse response. In the presence of noise the algorithm permits to easily separate signal from noise number based on the relative values of the singular values, Juang and Pappa (1986) proposed two quantitative criteria to eliminate frequencies created by measurement noise. In a nonlinear case, the ERA algorithm would deliver a linearized model whose order can be defined based on the most significant singular values. In any case, the singular values set is a clean image of the plant dynamics and can be used to detect an identify plant parameter changes. For the sake of simplicity and without lost in the argument, this work focuses on the original algorithm. In the following, all posterior algorithm improvements and details of the derivation have been omitted.

Consider a state space realization for a linear time-invariant discrete-time dynamic system given by

$$x(k+1) = A(\theta)x(k) + B(\theta)u(k) \; ; \qquad y(k) = C(\theta)x(k) + v(k) \tag{1}$$

where, [A,B,C] defines a discrete-time state space realization, x is a n-dimensional state vector, u an m-dimensional control input, y a p-dimensional measurement vector and v represents measurement noise.

The system impulse response sequence is given by

$$h(k) = \{\, h(0) \quad h(1) \quad h(2) \quad . \; . \; . \; . \; . \; . \,\} \;\; or \qquad h(k+1) = y(k+1) = C\,A^k\,B \tag{2}$$

thus, a Hankel matrix can be constructed from the impulse response sequence as

$$H(k) = \begin{bmatrix} h(k+1) & h(k+2) & h(k+3) & . \\ h(k+2) & h(k+3) & h(k+4) & . \\ h(k+3) & h(k+4) & h(k+5) & . \\ . & . & . & . \\ . & . & . & . \end{bmatrix} = \begin{bmatrix} CA^kB & CA^{k+1}B & CA^{k+2}B & . \\ CA^{k+1}B & CA^{k+2}B & CA^{k+3}B & . \\ CA^{k+2}B & CA^{k+3}B & CA^{k+4}B & . \\ . & . & . & . \\ . & . & . & . \end{bmatrix} \tag{3}$$

with

$$H(0) = \begin{bmatrix} CB & CA^1B & CA^2B & . & . \\ CA^1B & CA^2B & CA^3B & . & . \\ CA^2B & CA^3B & CA^4B & . & . \\ . & . & . & . & . \\ . & . & . & . & . \end{bmatrix} = \begin{bmatrix} \overline{C} \; \overline{B} \end{bmatrix} \; where \;\; \overline{C} = \begin{bmatrix} C \\ CA \\ CA^2 \\ . \\ . \\ CA^{n-1} \end{bmatrix} \; \& \; \overline{B} = \begin{bmatrix} B & AB & A^2B & . & . & A^{n-1}B \end{bmatrix} \tag{4}$$

it can be shown that

$$h(k+1) = E_p{}^T H(k) E_m = E_p{}^T \,\overline{C} A^k \overline{B}\, E_m = \left[E_p{}^T\right]\left[PD\right]\left[D^{-1}P^T\right]\left[H(k)\right]\left[QD^{-1}\right]\left[DQ^T\right]\left[E_m\right] \tag{5}$$

and also that

$$h(k+1) = y(k+1) = C A^k B = \left[E_p{}^T P D^{1/2}\right]\left[D^{-1/2} P^T H(1) Q D^{-1/2}\right]^k \left[D^{1/2} Q^T E_m\right] \tag{6}$$

finally, Juang and Pappa shown that a minimal order realization could be found as

$$C = \left[E_p{}^T P D^{1/2}\right] \qquad A = \left[D^{-1/2} P^T H(1) Q D^{-1/2}\right] \qquad B = \left[D^{1/2} Q^T E_m\right] \tag{7}$$

4. THE SINGULAR VALUE BASED FAULT DETECTION AND ISOLATION (SVFDI) ALGORITHM

The proposed SVFDI algorithm can be seen as a generalization of the ERA algorithm (originally applied for model identification). It will be shown later that in the case of the SVFDI problem there is no need for a plant model, all one needs is the singular values set of the Hankel matrix built from the plant time response, as shown in the previous section. The choice of singular values as a measure to detect parametric drift is because its nature (real positive numbers) does not change as natural frequencies and eigenvalues do when plant parameters change. Under "normal" operational conditions any change of plant parameters values would affect the system dynamics and in a final analysis the singular values of the Hankel matrix. In this context, the set of singular values can be considered a natural choice for detecting parametric drifts and failures. The singular values set can be interpreted as an image of the plant parameters. Assuming this fact, and in a worst case scenario, a relationship between the singular values and the plant parameters can be established using standard correlation analysis (when required) and use these chosen singular values as "flags" to indicate any parameter drift from its nominal value. The correlation analysis would deliver a mapping of the plant parameters drifts into the singular values set of the Hankel matrix built from the plant time response. The proposed procedure for fault detection and isolation is depicted in the following section through examples.

5. EXPERIMENTAL RESULTS

To illustrate the features of the proposed technique, a DC-Motor computational model package is used in this work (Palhares, 2011). Several undesired events may affect the performance of DC motors, the used model allows the simulation of faults due to: Armor Current Sensor Failure, Field Current Sensor Failure, Velocity Sensor Failure, Armor Coil Break, Field Coil Break, Short Circuit of the Armor Feed Static Converter, Short Circuit of the Field Feed Static Converter, Short Circuit of the Field Coil, Short Circuit of the Armor Coil, Cooling System Failure and Bearing Lubrication Failure. The last three cases are used in this work for simulation purposes. In this case, the plant is defined by a set of non-linear differential equations given by:

$$\begin{cases} \dfrac{di_a}{dt} = \dfrac{1}{L_a}\left(v_a - r_a\, i_a - e_a\right) \\ \dfrac{di_{fd}}{dt} = \dfrac{1}{L_{fd}}\left(v_{fd} - r_{fd}\, i_{fd}\right) \\ \dfrac{d\omega_r}{dt} = \dfrac{1}{j_m}\left(T_{em} - B_m\, \omega_r - T_L\right) \end{cases} \quad ; \qquad \text{with} \quad \begin{cases} e_a = L_{afd}\, i_{fd}\, \omega_r \\ T_{em} = L_{afd}\, i_{fd}\, i_a \end{cases} \tag{8}$$

where

r_a	=	Armor circuit resistance
r_{fd}	=	Field circuit resistance
L_a	=	Armor circuit inductance
L_{fd}	=	Field circuit inductance
L_{afd}	=	Armor/field mutual inductance
e_a	=	Armor counter emf
T_{em}	=	Electromagnetic torque
T_L	=	Torque due to the load
B_m	=	Viscous attrition coefficient
J_m	=	Moment of inertia of the motor-load system

or in matrix form

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} -\frac{r_a}{L_a} & -\frac{L_{afd}}{L_a}x_3 & 0 \\ 0 & -\frac{r_{fd}}{L_{fd}} & 0 \\ -\frac{L_{afd}}{J_m}x_2 & 0 & -\frac{B_m}{J_m} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} \frac{1}{L_a} & 0 \\ 0 & \frac{1}{L_{fd}} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_a \\ v_{fd} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \begin{bmatrix} T_L \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}; \qquad \text{and} \qquad \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} i_a \\ i_{fd} \\ \omega_r \end{bmatrix} \tag{9}$$

Table 1 shows the DC-motor parameter values used for simulation purposes.

Table 1. DC Motor Parameters - Nominal Values			
R_a	=	4.6e-3	Armor circuit resistance
R_{fd}	=	12.1875	Field circuit resistance
L_a	=	2.38e-4	Armor circuit inductance
L_{fd}	=	8.750	Field circuit inductance
L_{afd}	=	0.23	Armor/field mutual inductance
J_m	=	2580	Moment of inertia of the motor-load system
V_a	=	750	Armor circuit feeding voltage
V_{fd}	=	750	Field circuit feeding voltage
I_a	=	17098	Armor circuit current
B_m	=	127	Viscous attrition coefficient
I_{fd}	=	61.48	Field circuit current

The basis of the ERA algorithm, initially proposed as a modeling technique from the plant impulse response, is used here. The singular values are a reliable mapping of the plant dynamics. Whenever a plant model is not required (the SVFDI case) the step response can also be used to built a set of singular values and to establish a correlation between this set and the plant parameters under supervision. It should be mention that the set of singular values of the Hankel matrix, in either case (step or impulse response), is unique.

An important feature of the SVFDI algorithm (Galvez, 2008) used in this work is that its formulation eliminates the need for a plant model. Having obtained a nominal plant image (through the singular values of the Hankel matrix obtained from the plant time response), this image can be used to determine, by comparison, any value drift of a plant parameter, as it will be shown next.

For simulation purposes, a DC-motor model available in Palhares (2011) has been adapted and used through the experiment, the SVFDI algorithm was tested to detect and identify failures that causes continuous time Reponses on the plant output. Three output variables have been monitored and used in the experiment: armor current, field current and velocity.

Figure 1. shows the DC Motor nominal (no failure) step and impulse time responses. Figures 2 through 4 present experimental results for three types of DC-Motor failures. Figure 2; shows a short circuit of the armor coil time responses; Figure 3 presents a cooling system failure time responses; and Figure 4 shows a bearing lubrication failure time responses. In all of them step and impulse responses have been considered.

Hankel matrices have been built from the time responses (step and impulse) for every simulated failure and their six first singular values computed. The obtained singular values were normalized following the algorithm presented in Section 6. The results are graphically displayed in Figures 5 and 6.

These last results are the basis for the SVFDI algorithm. The normalized singular values are a unique mapping of the plant dynamics and so they reflect any change on the plant parameters. Finally, simple techniques, such as correlation analysis and Boolean algebra, may be used to establish “flags” related to plant parameters failures.

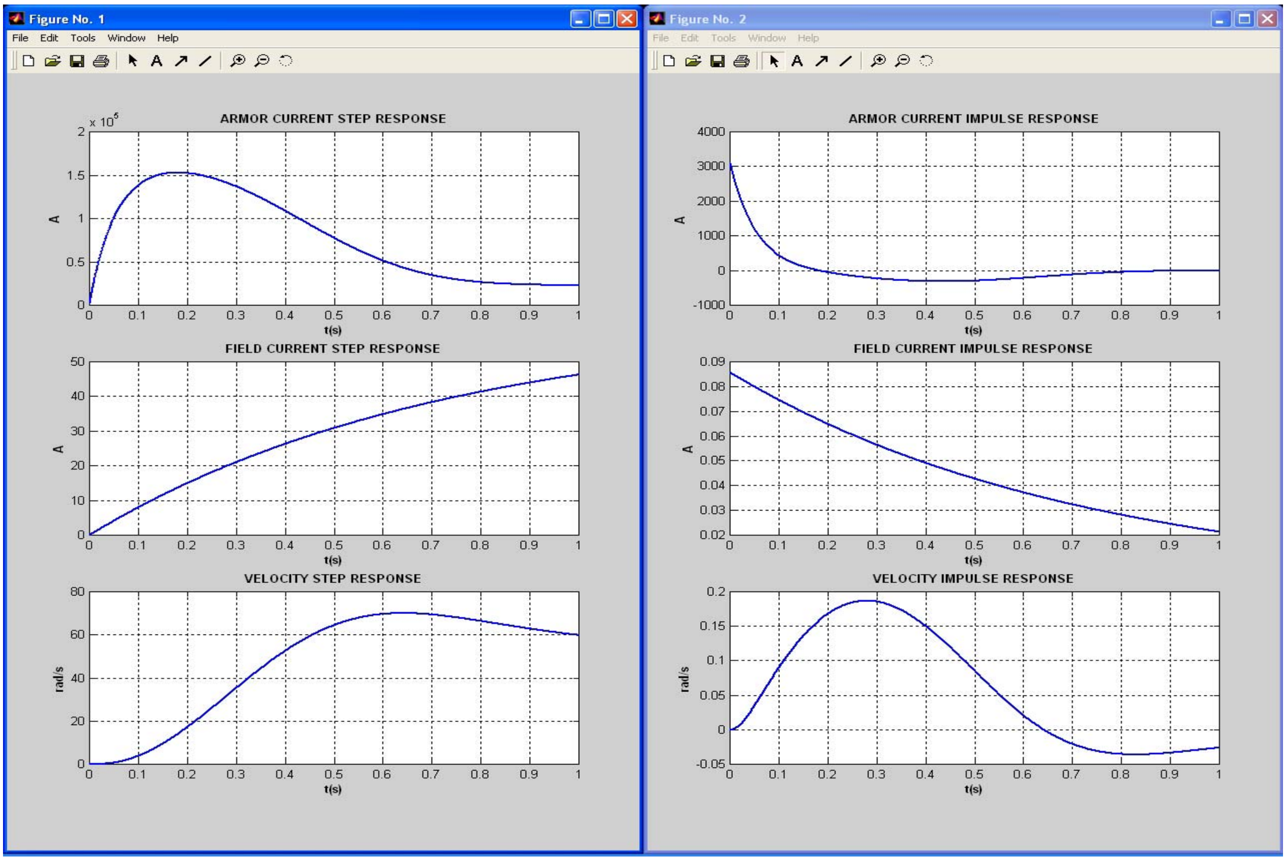

Figure 1. The DC Motor Nominal Time Responses.

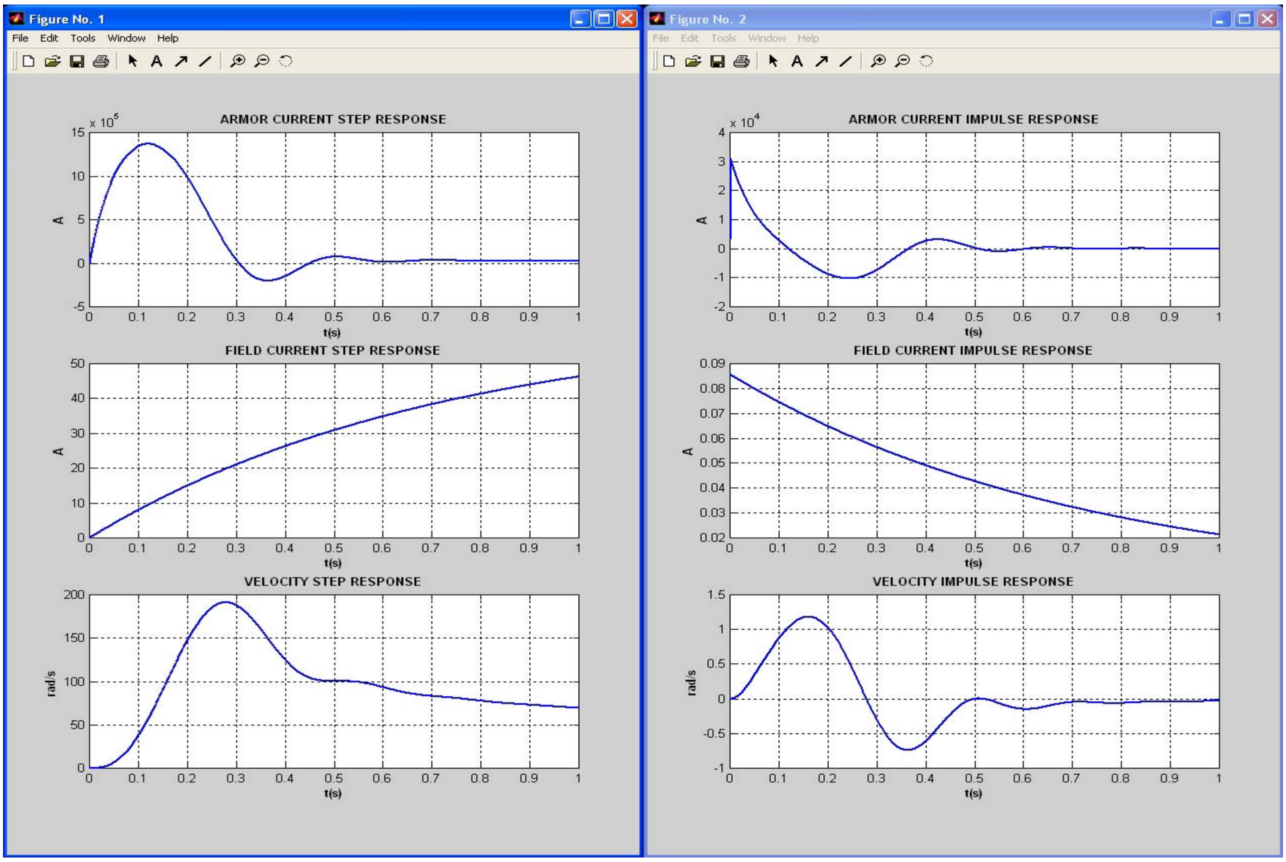

Figure 2. Short Circuit of the Armor Coil - Time Responses.

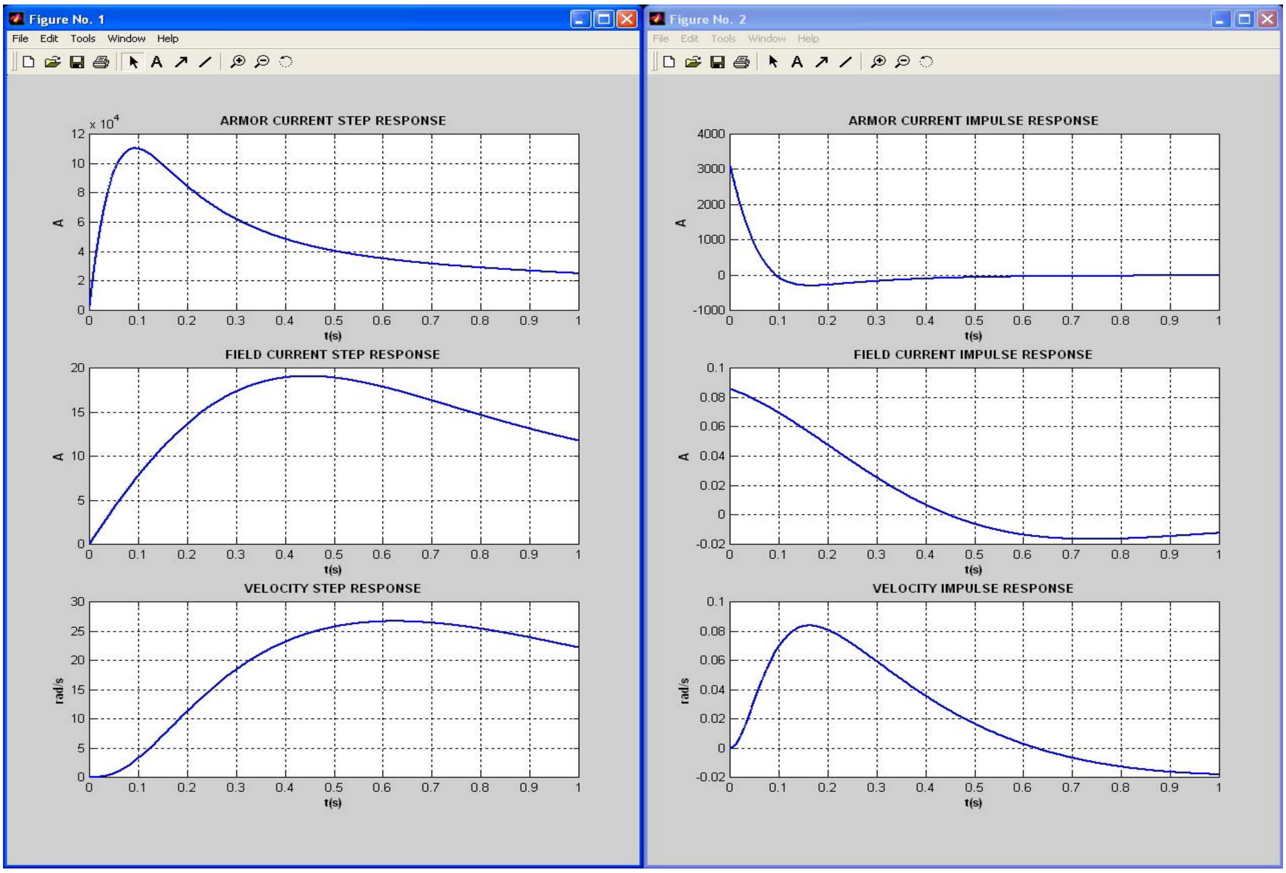

Figure 3. Cooling System Failure - Time Responses.

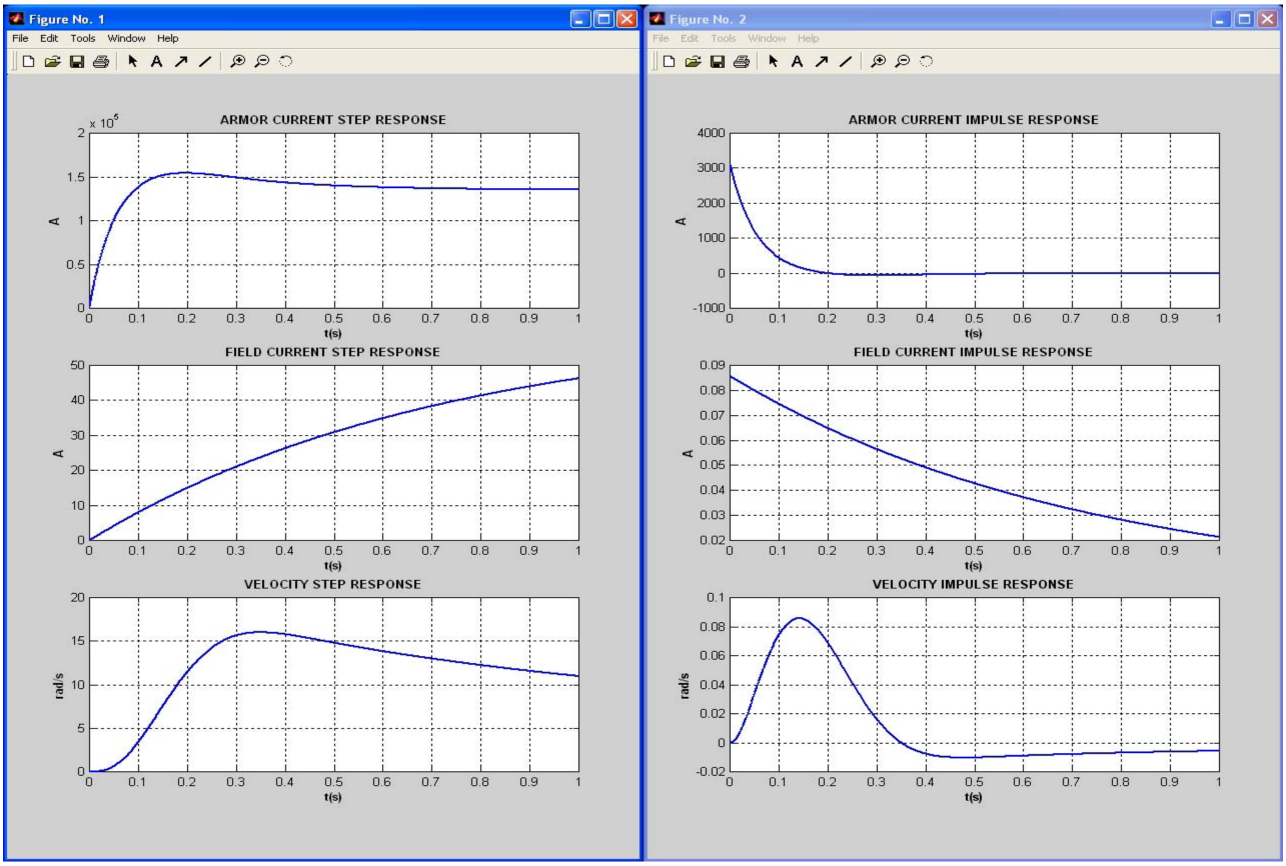

Figure 4. Bearing Lubrication Failure – Time Responses.

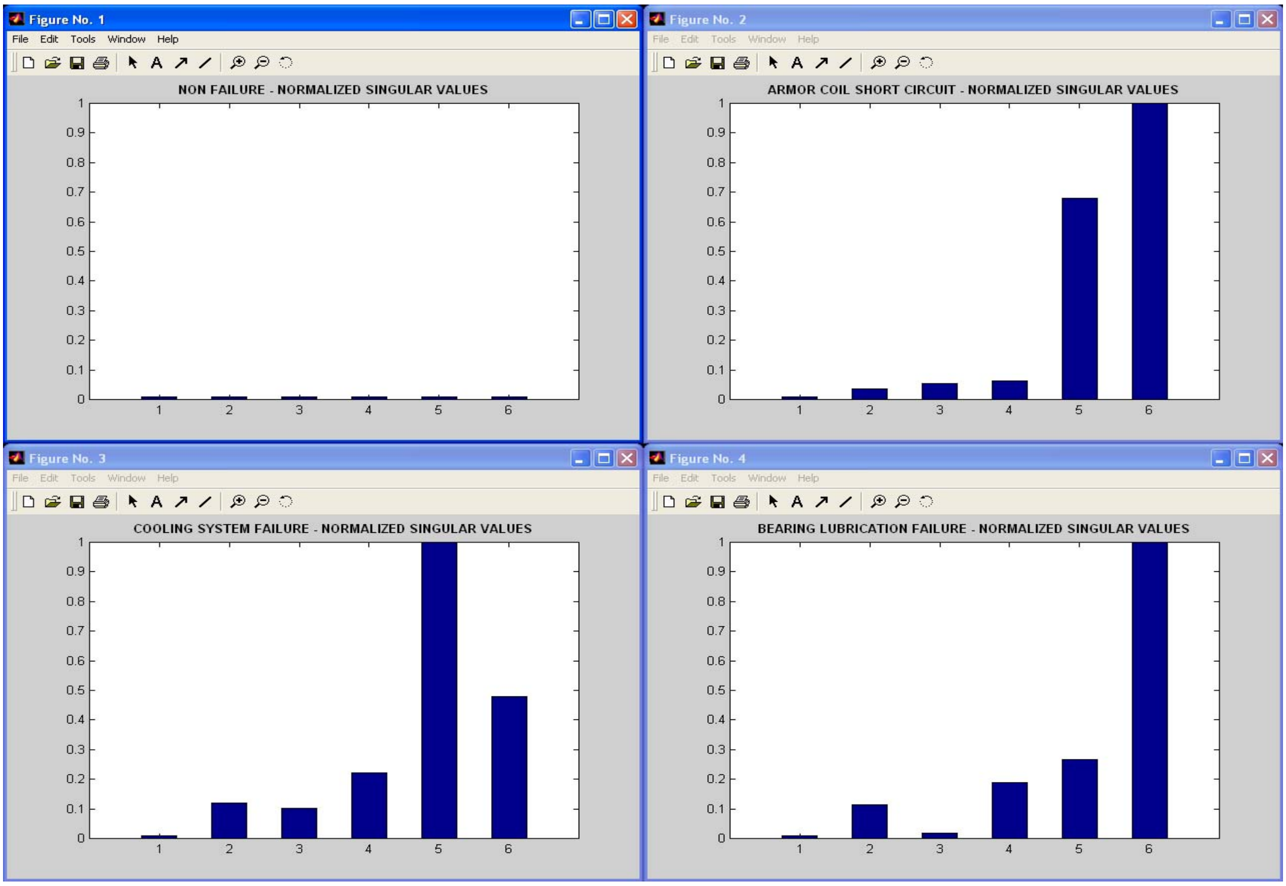

Figure 5. Normalized Singular Values from the Impulse Responses.

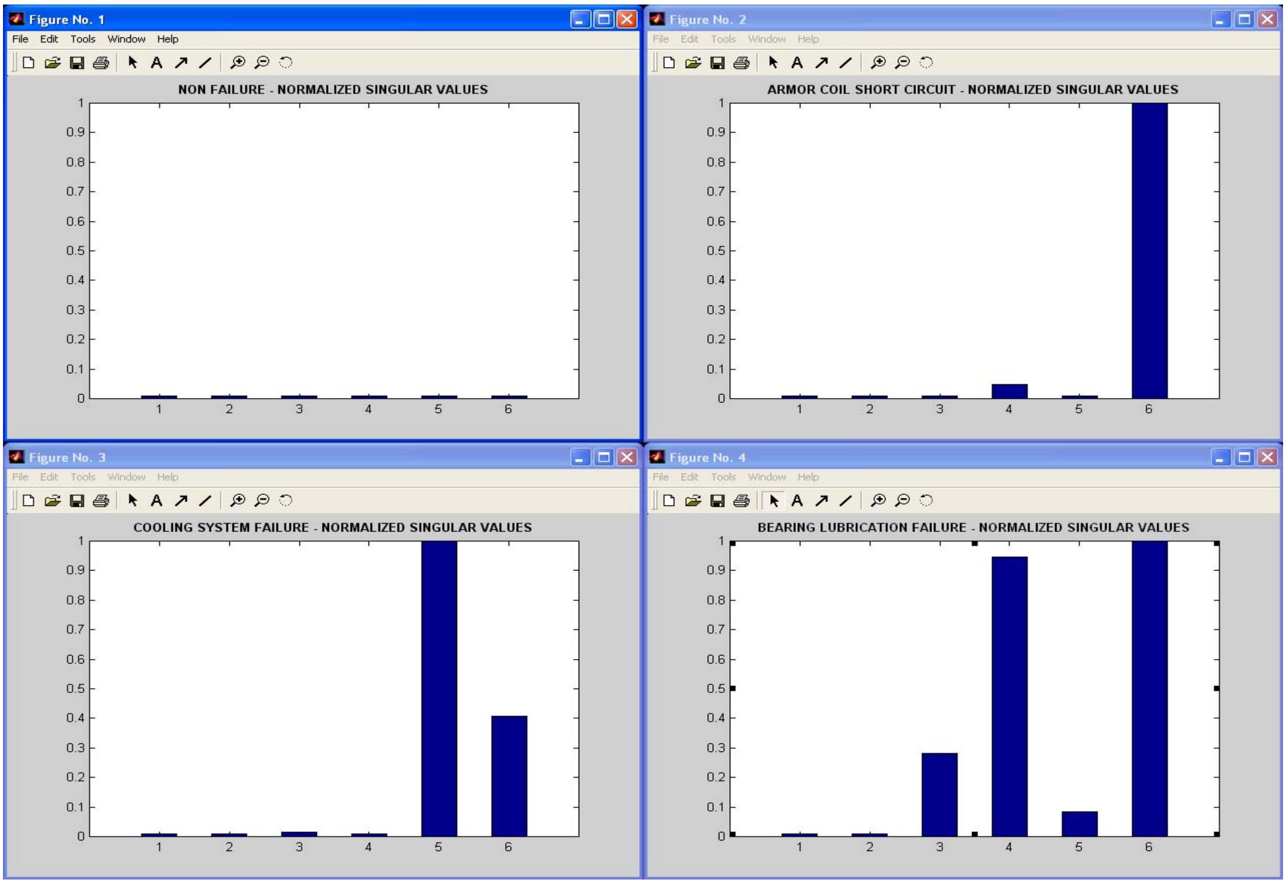

Figure 6. Normalized Singular Values from the Step Responses.

6. DETERMINING THE FDI "FLAGS"

This section shows a simple procedure for finding FDI indicators ("flags") from the plant time responses. The proposed technique delivers reliable results for fault detection and fault isolation. Initially, the time response (step or impulse response) of the plant is experimentally obtained. Next, a Hankel matrix from plant output is built and its singular values computed. Table 2 presents the systems eigenvalues for the plant impulse response and Table 3 shows the singular values of the plant when a step response is used.

Table 2. Singular Values for Impulse Response

	SV1	*SV2*	*SV3*	*SV4*	*SV5*	*SV6*
Non Failure	78439.787	6059.686	194.863	3.482	0.017	0.000
Armor Coil Short Circuits	754891.744	529686.607	25469.754	541.949	27.518	1.226
Cooling System Failure	60412.753	24555.109	702.129	22.967	0.436	0.006
Bearing Lubrication Failure	78691.997	3545.554	181.717	5.855	0.033	0.002

Table 3. Singular Values for Step Response

	SV1	*SV2*	*SV3*	*SV4*	*SV5*	*SV6*
Non Failure	17330401.104	1555279.002	20316.257	171.501	2.503	0.016
Armor Coil Short Circuits	149646621.157	22665218.511	1006893.746	73130.014	228.479	140.620
Cooling System Failure	12293745.941	1378094.726	40575.928	204.498	156.567	0.417
Bearing Lubrication Failure	17401207.234	1526923.002	5967.910	578.197	3.033	0.056

From Tables 2 and 3, a set of normalized singular values can be found following the algorithm:

```
NORMSV = abs ((Perturbed SV-Nominal SV) / Nominal SV)
NORMSV = NORMSV / max (NORMSV)
if  NORMSV ≤ 0.01 then
    NORMSV = 0.01
 End
```

The results are depicted on Tables 4 (for impulse response) and 5 (for step response) that show the normalized singular values.

Table 4. Normalized Singular Values for Impulse Response

	NORMSV1	*NORMSV2*	*NORMSV3*	*NORMSV4*	*NORMSV5*	*NORMSV6*
Non Failure	0.01	0.01	0.01	0.01	0.01	0.01
Armor Coil Short Circuits	0.01	0.03	0.05	0.06	0.68	1.00
Cooling System Failure	0.01	0.12	0.10	0.22	1.00	0.48
Bearing Lubrication Failure	0.01	0.11	0.02	0.19	0.26	1.00

Table 5. Normalized Singular Values for Step Response

	NORMSV1	*NORMSV2*	*NORMSV3*	*NORMSV4*	*NORMSV5*	*NORMSV6*
Non Failure	0.01	0.01	0.01	0.01	0.01	0.01
Armor Coil Short Circuits	0.01	0.01	0.01	0.05	0.01	1.00
Cooling System Failure	0.01	0.01	0.02	0.01	1.00	0.41
Bearing Lubrication Failure	0.01	0.01	0.28	0.94	0.08	1.00

In this case, Tables 4 and 5 can be used to select the best set of normalized singular values to be used as "flags" based on their correlation with plant parameters. Directly from Tables 4 and 5 one can build Table 6 and 7 that represent the structural sensitivity of the singular values with respect to parameter drifts.

Table 6. FDI Flags using an Impulse Test Signal.

	FLAG 1	*FLAG 2*	*FLAG 3*	*FLAG 4*	*FLAG 5*	*FLAG 6*
Armor Coil Short Circuits					1	1
Cooling System Failure					1	
Bearing Lubrication Failure						1

Table 7. FDI Flags using a Step Test Signal.

	FLAG 1	*FLAG 2*	*FLAG 3*	*FLAG 4*	*FLAG 5*	*FLAG 6*
Armor Coil Short Circuits						1
Cooling System Failure					1	
Bearing Lubrication Failure				1		1

In a more complex case, in which Tables 6 and 7 could not be directly built, standard regression analysis techniques can be used to establish the correlation coefficients between plant parameters and the singular values of the Hankel matrix. In that case the value of "1" can be assigned to the greatest coefficient and "0" to the smallest. The "ones" mean strong correlation and the "zeros" a weak or inexistent correlation as shown in Galvez (2009).

7. FINAL COMMENTS AND CONCLUSIONS

This paper explored the application of the SVFDI algorithm for fault detection and isolation on a DC-Motor parametric model. Two functional levels of the SVFDI procedure have been verified, namely alarm generation and alarm interpretation. At the alarm generation level (detection), the SVFDI algorithm naturally displays plant failure through the change of the singular values structure and values. At the alarm interpretation level (isolation), the SVFDI algorithm delivers an image of the plant parameters through the singular values allowing the identification of the faulty parameter. Finally, the SVFDI algorithm applied to a DC Motor model shown outstanding performance in solving both, fault detection and isolation problems.

8. ACKNOWLEDGEMENTS

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