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AN ALGORITHM FOR FAULT DETECTION FROM A SINGULAR VALUE DECOMPOSITION BASED TECHNIQUE

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Abstract. *This paper presents a novel technique for fault detection and isolation based on the singular value decomposition of a Hankel matrix, which is built from plant output measurements. The singular value based fault detection and isolation (SVFDI) algorithm uses the singular values of the Hankel matrix to detect and identify faulty plant parameters. It is shown that the detection (alarm generation) and isolation (alarm interpretation) tasks are easily permormed based on the SVFDI algorithm outputs. Simulation examples are finally presented to illustrate the performance and application of the proposed algorithm.*

Keywords*: Fault Detection and Isolation, Parameter Drift Detection, Singular Value Decomposition.*

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, control related techniques 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 and 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 plant models. 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 introduces the singular values based fault detection and isolation (SVFDI) algorithm; Section 5 explores the SVFDI algorithm features through experimental results; and finally, Section 6 presents final comments and conclusions.

2. SOME COMMENTS ON THE FDI PROBLEM

In general, 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 normal 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 SHORT REVIEW

This section presents the basic formulation of the Eigensystem Realization Algorithm (ERA), as originally proposed by Juang and Pappa in 1985. Since then, the scientific community has proposed several modifications and improvements. The ERA algorithm is a very reliable computational procedure originally proposed for modeling of dynamic systems. 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 less important derivation steps and several results have been omitted.

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

$$\begin{aligned} x(k+1) &= A(\theta)x(k) + B(\theta)u(k) \\ y(k) &= C(\theta)x(k) + v(k) \end{aligned} \tag{1}$$

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

$$h(k) = \{\, h(0) \quad h(1) \quad h(2) \quad h(3) \quad . \; . \; . \; . \; . \,\} \tag{2}$$

in compact form, it can be written as

$$h(k+1) = y(k+1) = C\,A^k\,B \tag{3}$$

A Hankel matrix can be constructed from the impulse response sequence as

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

also

$$H(0) = \begin{bmatrix} CB & CA^1B & CA^2B & . & . \\ CA^1B & CA^2B & CA^3B & . & . \\ CA^2B & CA^3B & CA^4B & . & . \\ . & . & . & . & . \\ . & . & . & . & . \end{bmatrix} = \begin{bmatrix} \overline{C} & \overline{B} \end{bmatrix} \tag{5}$$

it should be noted that, usually, *H(0)* is not square and that $dim\big(H(0)\big) = np$ x nm and $rank\big(H(0)\big) \le n$ and also,

$$\overline{C} = \begin{bmatrix} C \\ CA \\ CA^2 \\ . \\ . \\ CA^{n-1} \end{bmatrix} \qquad \& \qquad \overline{B} = \begin{bmatrix} B & AB & A^2B & . & . & A^{n-1}B \end{bmatrix} \tag{6}$$

From the singular value decomposition (SVD)

$$H(0) = M \Sigma N^T = M \left[\begin{array}{c|c} D & 0 \\ \hline 0 & 0 \end{array} \right] N^T = M \left[\frac{In}{0} \right] D [In \mid 0] N^T \qquad (7)$$

then

$$H(0) = PDQ^T = \overline{C}\,\overline{B} \qquad (8)$$

and

$$H^+ = N\Sigma^+ M^T = QD^{-1}P^T \qquad (9)$$

It is known that, there exist matrices Ep and Em such that

$$h(k+1) = Ep^T H(k) Em \qquad (10)$$

and that

$$H(k) = \overline{C} A^k \overline{B} \qquad (11)$$

and also that

$$\overline{C}\,\overline{B} = PDQ^T = H(0) \qquad (12)$$

then

$$h(k+1) = Ep^T H(k) Em = Ep^T \overline{C} A^k \overline{B} Em = [Ep^T][PD][D^{-1}P^T][H(k)][QD^{-1}][DQ^T][Em] \qquad (13)$$

hence

$$h(k+1) = [Ep^T PD^{1/2}][D^{-1/2}P^T H(1) QD^{-1/2}]^k [D^{1/2}Q^T Em] \qquad (14)$$

finally, a minimal order realization can be found as

$$\begin{aligned} C &= [Ep^T PD^{1/2}] \\ A &= [D^{-1/2}P^T H(1) QD^{-1/2}] \\ B &= [D^{1/2}Q^T Em] \end{aligned} \qquad (15)$$

Besides that, Juang and Pappa (1986) have also proposed two quantitative criteria to eliminate modal frequencies created by measurement noise.

4. THE SINGULAR VALUES 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 of the Hankel matrix built from the plant time response, as shown in the previous section.

In the following and for the purposes of the SVFDI algorithm we shall call an *observable plant parameter* if any drift from its nominal value can be detected from output measurements. Also, it is assumed that in a close neighborhood of its nominal value a parameter drift will “friendly” affect the singular values of the Hankel matrix. Finally, it is also clear that observability and controllability properties of the plant (as their standard definitions) also play important roles in the performance of the SVFDI algorithm.

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, it can be established a relationship between the singular values and the plant parameters using standard correlation analysis and use these singular values as flags to indicate any parameter drift from its nominal value.

The choice of singular values as a measure to detect parametric drift is due to the fact that 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.

It is worth to mention that in a statistic framework, correlation does not imply causality meaning that correlation cannot be validly used to infer a causal relationship between the variables. Consequently, correlation between two variables is a necessary but not a sufficient condition to establish a causal relationship.

However, having established causality, and in a close-enough neighborhood of the nominal plant, correlation can be taken as the natural choice for analysis. The correlation analysis will 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, two lumped parameter models have been chosen. Table 1 shows the parameter values used to build the following application examples.

Table 1. Parameter Values for Examples I and II

Parameter	Value	Parameter	Value	Parameter	Value
$m_1 =$	*1*	$d_1 =$	*0.0600*	$k_1 =$	*16*
$m_2 =$	*1*	$d_2 =$	*0.0200*	$k_2 =$	*6.0*
$m_3 =$	*1*	$d_3 =$	*0.0020*	$k_3 =$	*0.4*

- **<u>Application Example I:</u>**

Let us consider the spring-mass-dashpot system connected as shown in Fig. 1.

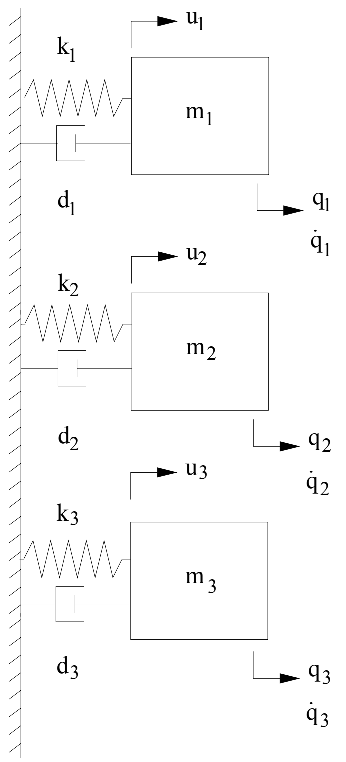

Figure 1. The Spring-Mass-Dashpot System for Example I

For the given model, the kinetic energy, potential energy and the Raleigh dissipation function are given by:

$$T = \frac{1}{2}\left\{ m_1 \dot{q}_1^{\,2} + m_2 \dot{q}_2^{\,2} + m_3 \dot{q}_3^{\,2} \right\}$$
$$V = \frac{1}{2}\left\{ k_1 q_1^{\,2} + k_2 q_2^{\,2} + k_3 q_3^{\,2} \right\}$$
$$R = \frac{1}{2}\left\{ d_1 \dot{q}_1^{\,2} + d_2 \dot{q}_2^{\,2} + d_3 \dot{q}_3^{\,2} \right\}$$

and the differential equations of motions by

$$m_1 \ddot{q}_1 + d_1 \dot{q}_1 + k_1 q_1 = u_1$$
$$m_2 \ddot{q}_2 + d_2 \dot{q}_2 + k_3 q_2 = u_2$$
$$m_3 \ddot{q}_3 + d_3 \dot{q}_3 + k_3 q_3 = u_3$$

in matrix form with $u_1 = u_2 = u_3 = u$

$$M \ddot{q} + D \dot{q} + K q = F u$$

where

$$M = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix} ; \quad D = \begin{bmatrix} d_1 & 0 & 0 \\ 0 & d_2 & 0 \\ 0 & 0 & d_3 \end{bmatrix} ; \quad K = \begin{bmatrix} k_1 & 0 & 0 \\ 0 & k_2 & 0 \\ 0 & 0 & k_3 \end{bmatrix} ; \quad F = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

then, a state space representations can be written as

$$\dot{x} = [A]\, x + [B]\, u \qquad \textit{with} \quad x = \begin{bmatrix} q \\ \dot{q} \end{bmatrix}$$
$$y = [C]\, x$$

where

$$\dot{x} = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}D \end{bmatrix} x + \begin{bmatrix} 0 \\ M^{-1}F \end{bmatrix} u \qquad \textit{with} \quad x = \begin{bmatrix} q \\ \dot{q} \end{bmatrix}$$

$$y = \begin{bmatrix} I & 0 \end{bmatrix} x$$

then

$$\dot{x} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ -16.0000 & 0 & 0 & -0.0600 & 0 & 0 \\ 0 & -6.0000 & 0 & 0 & -0.0200 & 0 \\ 0 & 0 & -0.4000 & 0 & 0 & -0.0020 \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix} u$$

$$y = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} x \qquad \textit{with} \quad x = \begin{bmatrix} q \\ \dot{q} \end{bmatrix}$$

- **Application Example II:**

As a second example, let's consider the system presented in Fig. 2.

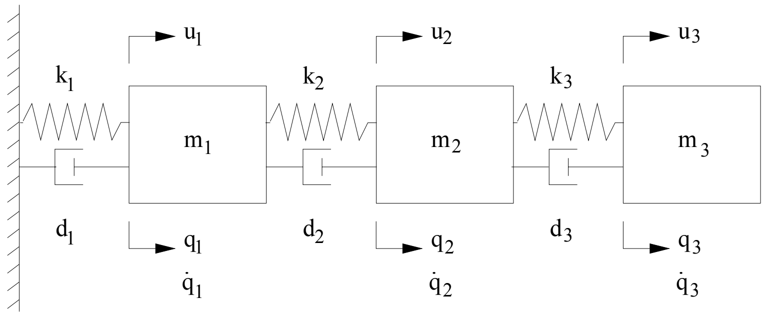

Figure 2. The Spring-Mass-Dashpot System for Example II

In this case, the kinetic energy, potential energy and the Raleigh dissipation function are given by:

$$T = \frac{1}{2}\left\{m_1\,\dot{q}_1^{\;2} + m_2\,\dot{q}_2^{\;2} + m_3\,\dot{q}_3^{\;2}\right\}$$
$$V = \frac{1}{2}\left\{k_1\,q_1^{\;2} + k_2(q_2 - q_1)^2 + k_3(q_3 - q_2)^2\right\}$$
$$R = \frac{1}{2}\left\{d_1\,\dot{q}_1^{\;2} + d_2(\dot{q}_2 - \dot{q}_1)^2 + d_3(\dot{q}_3 - \dot{q}_2)^2\right\}$$

and the differential equations of motions by

$$m_1\,\ddot{q}_1 + (d_1 + d_2)\dot{q}_1 - d_2\,\dot{q}_2 + (k_1 + k_2)q_1 - k_2\,q_2 = u_1$$
$$m_2\,\ddot{q}_2 - d_2\,\dot{q}_1 + (d_2 + d_3)\dot{q}_2 - d_3\,\dot{q}_3 - k_2\,q_1 + (k_2 + k_3)q_2 - k_3\,q_3 = u_2$$
$$m_3\,\ddot{q}_3 - d_3\,\dot{q}_2 + d_3\,\dot{q}_3 - k_3\,q_2 + k_3\,q_3 = u_3$$

in matrix form with $u_1 = u_2 = u_3 = u$

$$M\,\ddot{q} + D\,\dot{q} + K\,q = F\,u$$

where

$$M = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix};\quad D = \begin{bmatrix} d_1 + d_2 & -d_2 & 0 \\ -d_2 & d_2 + d_3 & -d_3 \\ 0 & -d_3 & d_3 \end{bmatrix};\quad K = \begin{bmatrix} k_1 + k_2 & -k_2 & 0 \\ -k_2 & k_2 + k_3 & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix};\quad F = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

then

$$\dot{x} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ -22.0000 & 6.0000 & 0 & -0.0800 & 0.0200 & 0 \\ 6.0000 & -6.4000 & 0.4000 & 0.0200 & -0.0220 & 0.0020 \\ 0 & 0.4000 & -0.8000 & 0 & 0.0020 & -0.0040 \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix} u$$

$$y = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} x \qquad with \quad x = \begin{bmatrix} q \\ \dot{q} \end{bmatrix}$$

It should be notice that in both examples the plant observability matrix is ill conditioned as shown in Tab. 2. Despite of that the proposed technique still delivers good results as it is shown later.

Table 2. Conditioning Numbers for Examples I and II

Uncoupled System Observability Matrix Conditioning Number	Coupled System Observability Matrix Conditioning Number
$\gamma = 249.2320$	$\gamma = 454.7896$

Figures 3 through 6 present several dynamic results of the plants used in the Examples I and II. They are placed side by side for comparison purposes. The Hankel matrix in both cases was built from the results shown in Figures 3a and 3b respectively.

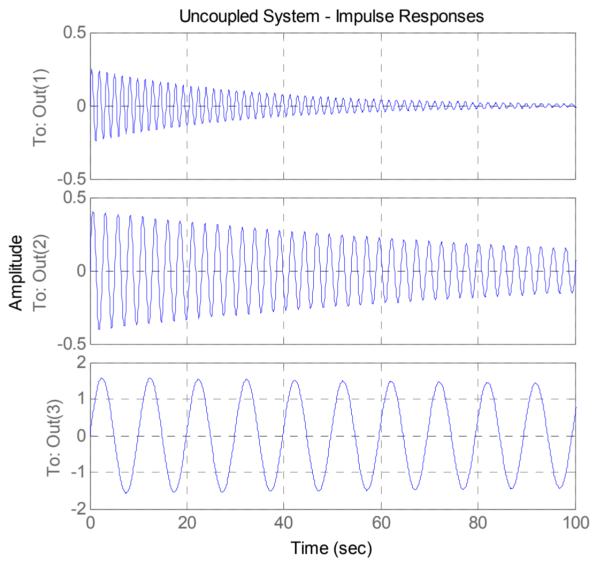

Figure 3a. Impulse Responses for Example I

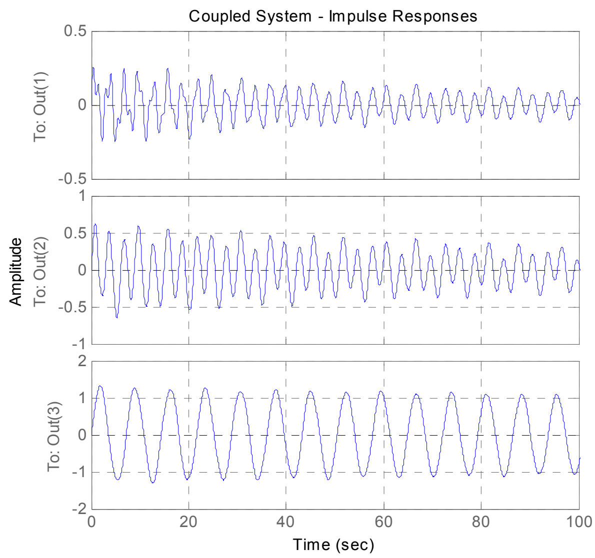

Figure 3b. Impulse Responses for Example II

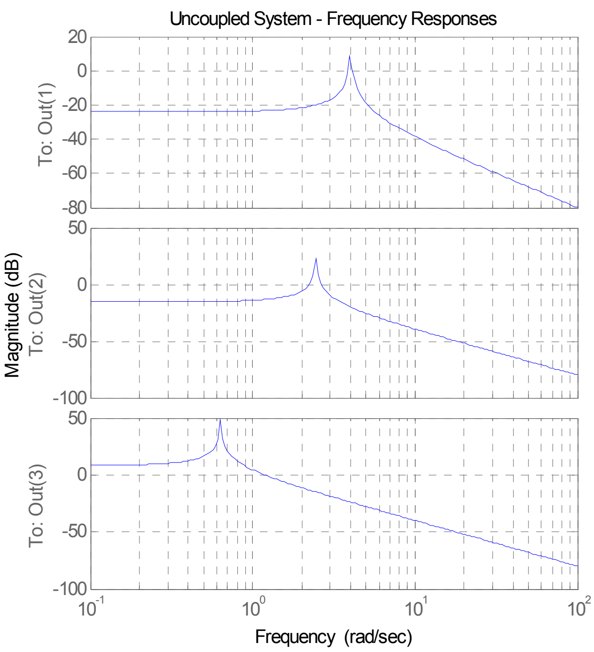

Figure 4a. Frequency Responses for Example I

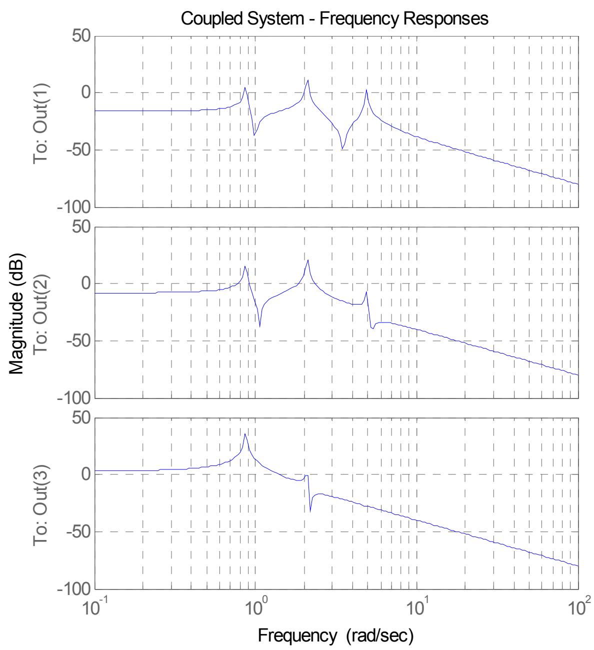

Figure 4b. Frequency Responses for Example II

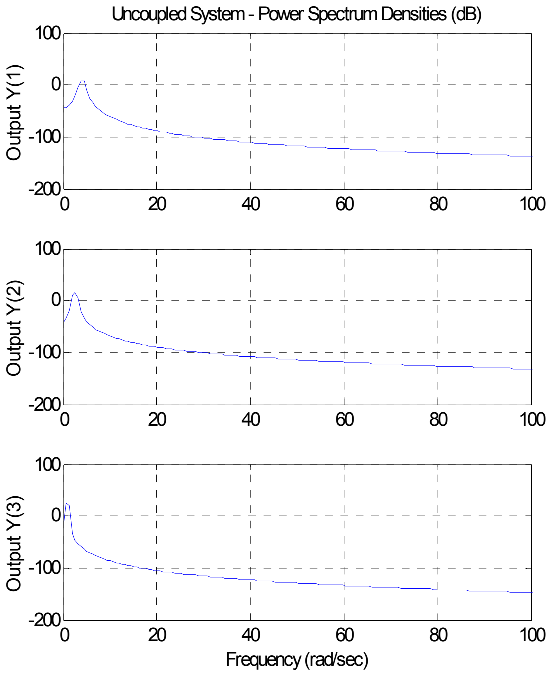

Figure 5a. Power Spectrum Densities for Example I

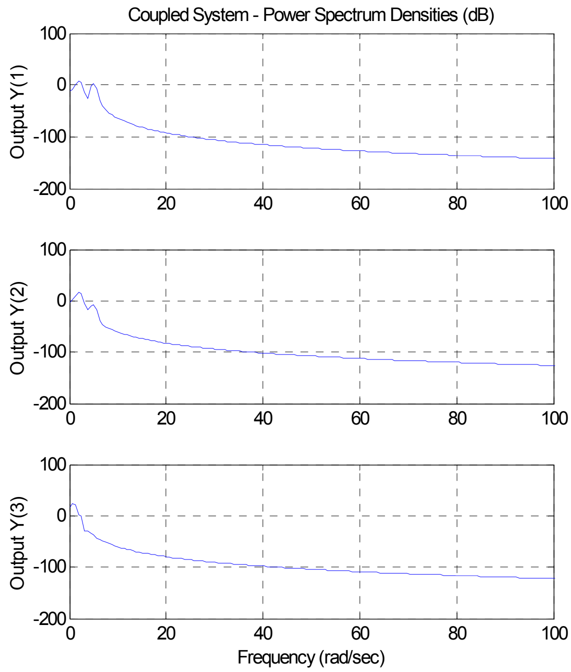

Figure 5b. Power Spectrum Densities for Example II

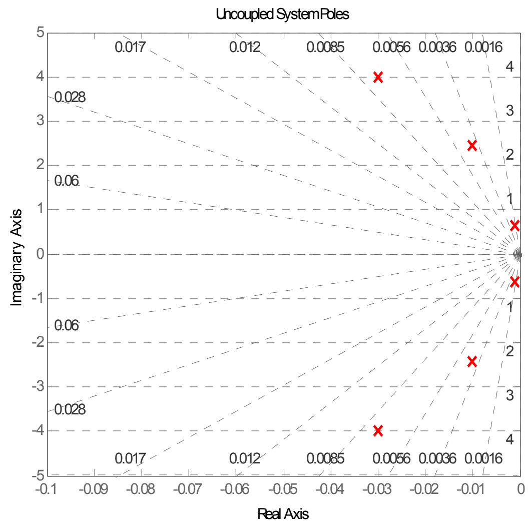

Figure 6a. System Poles for Example I

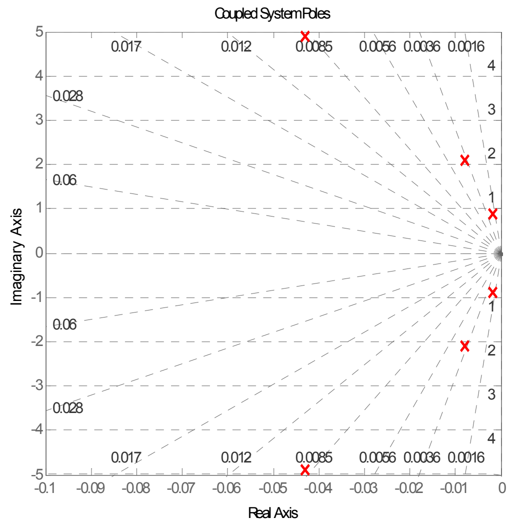

Figure 6b. System Poles for Example II

Table 3 presents the systems eigenvalues. Table 4 shows the nominal singular values of the plants.

Table 3. System Eigenvalues for Examples I and II

Uncoupled System – Eigenvalues	Coupled System - Eigenvalues
$\lambda_1 = -0.0300 + j\,3.9999$	$\lambda_1 = -0.0431 + j\,4.9030$
$\lambda_2 = -0.0300 - j\,3.9999$	$\lambda_2 = -0.0431 - j\,4.9030$
$\lambda_3 = -0.0100 + j\,2.4495$	$\lambda_3 = -0.0080 + j\,2.0974$
$\lambda_4 = -0.0100 - j\,2.4495$	$\lambda_4 = -0.0080 - j\,2.0974$
$\lambda_5 = -0.0010 + j\,0.6325$	$\lambda_5 = -0.0019 + j\,0.8715$
$\lambda_6 = -0.0010 - j\,0.6325$	$\lambda_6 = -0.0019 - j\,0.8715$

Table 4. System Singular Values for Examples I and II

Singular Values for the Uncoupled System	Singular Values for the Coupled System
$\sigma_1 =$ 56.4659	$\sigma_1 =$ 46.4186
$\sigma_2 =$ 51.7111	$\sigma_2 =$ 39.5797
$\sigma_3 =$ 0.1352	$\sigma_3 =$ 24.5874
$\sigma_4 =$ 0.0000	$\sigma_4 =$ 24.1515
$\sigma_5 =$ 0.0000	$\sigma_5 =$ 10.6838
$\sigma_6 =$ 0.0000	$\sigma_6 =$ 6.9848

Using standard regression analysis techniques, the correlation coefficients between plant parameters and the singular values of the plant output based Hankel matrix were calculated and normalized such that it has been assigned the value of "1" to the greatest coefficient and "0" to the smallest. The results are depicted on Tab. 5 that shows the normalized correlation coefficients between plant parameters and the singular values of the Hankel matrix for both examples. The "ones" mean strong correlation and the "zeros" a weak or inexistent correlation.

Table 5. Correlation Coefficients for Examples I and II

Correlation Coefficients for Uncoupled System

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
M_1	0.9014	1	0.3533	0.0825	0	0.0766
D_1	1	1	1	0.7136	0	0.3777
K_1	0.9638	1	0	0.3411	0.5061	0.5920

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
M_2	0.6571	0.6571	0.6571	0.7383	0	1
D_2	1	1	1	0.6552	0	0.2040
K_2	0.0295	0.0295	0.0295	1	0	0.7824

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
M_3	0.2000	0.2000	0.2000	0	1	0.4783
d_3	1	1	1	0	0.5160	0.4836
K_3	0.1018	0.1018	0.1018	0.9599	1	0

Correlation Coefficients for the Coupled System

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_1	0.1573	0	0.4929	0.4240	1	0.9050
d_1	0.7229	1	0.7304	0.6243	0	0.2977
k_1	1	0.8384	0	0.7924	0.9313	0.6100

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_2	1	0.9941	0.4138	0.3606	0	0.3907
d_2	0.8411	0.9746	0.6043	0.4854	0	1
k_2	0	0.5938	0.9933	1	0.6442	0.1995

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_3	0.6912	0.7102	1	0.4055	0	0.8637
d_3	0.4788	0.6470	0.9994	1	0.4091	0
k_3	0.9978	1	0	0.9978	0.9762	0.9540

Table 5 can be used to select the best singular values to be used as "flags" based on their correlation with plant parameters. Finally, from Tab. 5 one can built Tab. 6 that presents the structural sensitivity of the singular values with respect to parameter drifts.

Table 6. Structural Sensitivity Coefficients for Examples I and II

Structural Sensitivity Coefficients for the Uncoupled System

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_1		1				
d_1	1	1	1			
k_1	1	1				

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_2						1
d_2	1	1	1			
k_2				1		

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_3					1	
d_3	1	1	1			
k_3				1	1	

Structural Sensitivity Coefficients for the Coupled System

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_1					1	
d_1		1				
k_1	1					

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_2	1	1				
d_2		1				1
k_2			1	1		

	SV1	***SV2***	***SV3***	***SV4***	***SV5***	***SV6***
m_3			1			
d_3			1	1		
k_3	1	1		1	1	1

6. FINAL COMMENTS AND CONCLUSIONS

This paper presented a fault detection and isolation algorithm based on the singular value decomposition of the plant output. In a close neighborhood of the nominal plant values the regression analysis has shown to be the proper choice to link the Hankel matrix singular values with the plant parameters.

An important feature of the SVFDI algorithm 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; this image can be used to determine, by comparison, any value drift of the plant parameters.

Two functional levels of SVFDI procedure have been distinguished, 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 proposed SVFDI algorithm was applied to ill conditioning plants showing outstanding performance in solving both, detection and isolation problems.

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9. RESPONSIBILITY NOTICE