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Detection of gear faults via a dynamical sparse recovery method

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Abstract – Gear is one of the most important components in rotating machinery whose operation conditions directly modifies the whole performance of machinery. The presence of the gear failures may cause important perturbations in the operation machinery. Hence, it is necessary to detect the gear faults accurately at an early stage. This work deals with a new method of detection based on a dynamical sparse recovery algorithm. The gear power transmission is obtained by coupling the mechanical system, which is a single stage gear, with the electrical system, which is an asynchronous motor. For the electromechanical system, the sparse recovery method allows us to recover the mechanical faults from the electrical measurements. Moreover, from the same mechanical characteristics (temporal and frequency) it's possible to determine where the faults are present. More precisely, in our case, sparse recovery method is applied to estimate a sparse vector of possible faults in the gear-motor system respecting the condition that few non-zero faults happen simultaneously. In this paper, we will show some simulation results of the sparse recovery method that will be discussed with respect to the case of the gearbox driven by an induction motor.

Key words: Gear transmission / Faults detection / Sparse recovery Algorithm.

Introduction

Electro-mechanical systems such as geared transmissions driven by the electric motors are widely used in a number of industrial applications because of their reduced cost and high reliability. However, gear faults may be critical since they modify the machine performances and can lead to an interruption of the production. In this paper, a new method is presented in order to detect the gear faults. This diagnosis method is based on a Sparse Recovery Algorithm (SRA) that is able to find and reconstruct on-line a sparse vector of numerous possible faults.

Healthy model

The electro-mechanical system is a power transmission by gear obtained by coupling the mechanical system, which is a single stage gear, with the electrical system, which is an asynchronous motor [1]. For the mechanical part, the mathematical equations are obtained by developing the kinetic and potential energies of the gear element, based on the Lagrangian calculation. Concerning the electrical part, the equations of the asynchronous motor are obtained by using Kron's transformation. In order to obtain a unique differential system combining both electrical and mechanical state variables, we couple, in the same states vector, the electrical variables of the asynchronous motor with the mechanical ones related to the gear element. The principle of this coupling is to take into account the transmission ratio in the mechanical equation of the asynchronous motor. The coupled system leads to the following equations:

$$f = \begin{pmatrix} ai_{ds} + \omega_s i_{qs} + c\phi_{dr} + dq\omega_m \phi_{qr} + \frac{1}{L_s \sigma} V_{ds}, \\ -\omega_s i_{ds} + ai_{qs} - dq\omega_m \phi_{dr} + c\phi_{qr} + \frac{1}{L_s \sigma} V_{qs}, \\ ei_{ds} + f\phi_{dr} + (\omega_s - p\omega_m)\phi_{qr}, \\ ei_{qs} - (\omega_s - p\omega_m)\phi_{dr} + f\phi_{qr}, \\ \frac{1}{J} \left[\frac{pL_m}{L_r} (\phi_{dr} i_{qs} - \phi_{qr} i_{ds}) - \frac{\dot{\theta}_2}{\theta_1} C_r - f_1 \omega_m \right] \\ \dot{\theta}_1 \\ \dot{\theta}_2 \\ \frac{1}{I_1} \left[-K_{11}\theta_1 - K_{12}\theta_2 - C_{11}\dot{\theta}_1 - C_{12}\dot{\theta}_2 + I_1 \dot{\omega}_m \right] \\ + C_{em} \\ \frac{1}{I_2} \left[-K_{21}\theta_1 - K_{22}\theta_2 - C_{21}\dot{\theta}_1 - C_{22}\dot{\theta}_2 + I_1 \right] \\ \frac{R_{b1}}{R_{b2}} \dot{\omega}_m - C_r \end{pmatrix} \quad (1)$$

where:

K_{ij} (respectively, C_{ij}), $1 \leq i, j \leq 2$ are the stiffness (respectively, damping) matrix coefficients, $[\dot{i}_{ds} \ \dot{i}_{qs} \ \dot{\phi}_{dr} \ \dot{\phi}_{qr} \ \dot{\omega}_m \ \theta_1 \ \theta_2 \ \dot{\theta}_1 \ \dot{\theta}_2]^t \in \mathbb{R}^9$ is the state vector of the global electromechanical system is composed firstly by the two currents, the two fluxes and the rotational speed of the asynchronous machine and, secondly by the displacements and its derivatives of the gear and all other parameters are constants and depend on the machine characteristics. Since the electromechanical system is a nonlinear control-affine system, see (1), Sliding Mode Observers will be applied to monitor the dynamic behavior of the global system [1].

Faulty model

Numerous failures presented in the literatures can affect the gear [2]. In this paper, we introduce some mechanical faults (see, equation (2)) and we will next present a new method to detect them.

$$f = \begin{pmatrix} ai_{ds} + \omega_s i_{qs} + c\phi_{dr} + dq\omega_m \phi_{qr} + \frac{1}{L_s \sigma} V_{ds}, \\ -\omega_s i_{ds} + ai_{qs} - dq\omega_m \phi_{dr} + c\phi_{qr} + \frac{1}{L_s \sigma} V_{qs}, \\ ei_{ds} + f\phi_{dr} + (\omega_s - p\omega_m)\phi_{qr}, \\ ei_{qs} - (\omega_s - p\omega_m)\phi_{dr} + f\phi_{qr}, \\ \frac{1}{J} \left[\frac{pL_m}{L_r} (\phi_{dr} i_{qs} - \phi_{qr} i_{ds}) - \frac{\dot{\theta}_2}{\theta_1} C_r - f_1 \omega_m \right] \\ + \Delta C_r + \Delta f_1 \\ \dot{\theta}_1 + \Delta \theta_1 \\ \dot{\theta}_2 + \Delta \theta_2 \\ \frac{1}{I_1} \left[-K_{11}\theta_1 - K_{12}\theta_2 - C_{11}\dot{\theta}_1 - C_{12}\dot{\theta}_2 + I_1 \dot{\omega}_m \right] \\ + C_{em} + R_{b1} \cos(\beta) k(t) \delta_c \\ \frac{1}{I_2} \left[-K_{21}\theta_1 - K_{22}\theta_2 - C_{21}\dot{\theta}_1 - C_{22}\dot{\theta}_2 + I_1 \frac{R_{b1}}{R_{b2}} \right] \\ \dot{\omega}_m - C_r + R_{b2} \cos(\beta) k(t) \delta_c + \frac{\dot{e}}{R_{b2} \cos(\beta)} \end{pmatrix} \quad (2)$$

These defects can be classified as follows: 1) Mounting faults for example the gears eccentricity defect, 2) Form deviations: we introduce the cracks of the gears, 3) Sensors faults, and, 4) Operating faults, which can be the rotational speed variation of the motor, the Friction variation or the Load torque variation.

Sparse Recovery algorithm

Fault detection and estimation is highly simplified using the left-invertibility process. However, the left invertibility problem was processed just only in the case when the number of the unknown inputs

equal or fewer than the number of the measurements. In the contrary case, this problem has infinity of solutions. In particular, the Sparse Recovery (SR) method is able to find a simple representation of a signal using a specified dictionary Φ :

$$\chi = \Phi d(t) \quad (3)$$

where χ is the difference between the observer's measurements and the vector field of the proper system operation f and $d(t)$ is the unknown vector. It is assumed that $d(t)$ is s -sparse vector, i.e., no more than s components in $d(t)$ are non-zero. Moreover, s must be very low than p ($s \ll p$). The objective of the Sparse Recovery method is to reconstruct the faults vector $d(t)$ based on the measurement vector assuming that s verifies this condition:

$$2s+1 \leq m \quad (4)$$

The goal of the SR algorithm is to solve an optimization program that minimizes a cost function composed of mean squared error and the sparsity inducing terms. This sparse reconstruction problem is given by:

$$d^* = \arg \min_{d \in \mathbb{R}^p} \left\{ \frac{1}{2} \|\chi - \Phi d\|_2^2 + \lambda \|d\|_1 \right\} \quad (5)$$

In order to solve the optimization problem (5), a dynamical algorithm defined by (6), is proposed[3]:

$$\begin{cases} \tau \dot{u}(t) = -\Gamma u(t) + (\Phi^t \Phi - I_d) \hat{d}(t) - \Phi^t \chi^{-\alpha} \\ \hat{d}(t) = \varphi_\lambda(u(t)) \\ \Gamma^{-\alpha} = |\cdot|^\alpha \text{sign}(\cdot) \end{cases} \quad (6)$$

The output of the system (8) will converge to its equilibrium point u^* and the estimated of $d(t)$ converges in finite time to d^* .

Simulations

The simulations are carried on via Matlab/Simulink. The proposed method is firstly applied to the crack fault at $t=0.01s$ and with $s=1$. This fault is characterized by the appearance of the periodic peaks whose period is the number of teeth in the gear (Here, $Z_1=21$). The simulated non-zero fault is accurately recovered in finite time, while the estimated values of other zero faults converge to zero (see Figure1).

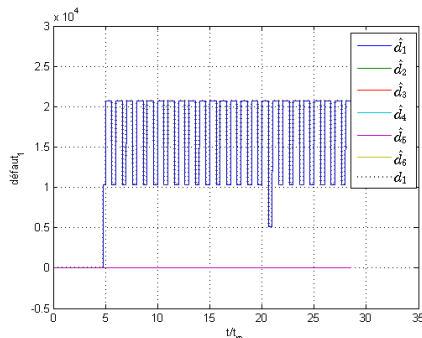


Figure 1. Case N1

In the case when $s=2$, as we can see in the Figure 2, sensors faults related to the two displacements of the gears are activated. This example confirms the condition (4) but the distinction between these faults is not always possible. All other defects converge to zero.

Figure 1. Style figure

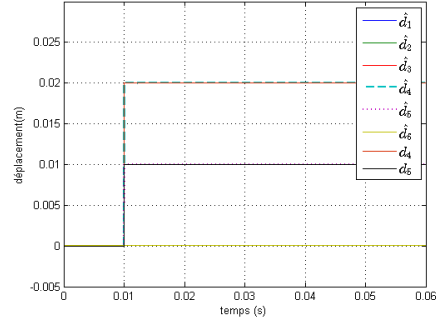


Figure 2. Case N2

Conclusions

In this paper, the gears power transmission models in healthy and faulty cases are presented. We have attempted to apply a sparse recovery algorithm to the system model under several faults. The simulation results, given in the last section, have proven the effectiveness of the proposed method to combine and recover on-line numerous faults. Thus, the future works would be focused on comparing this method with the other diagnostic methods.

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