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FAULT DETECTION BASED ON NOISE POWER ESTIMATION FOR CRYOGENIC COLD COMPRESSORS WITH ACTIVE MAGNETIC BEARINGS

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Abstract - This paper deals with the detection of faults in a cryogenic cold compressor equipped with active magnetic bearings (AMB). In particular, a fault detection technique based on noise power estimation is proposed. The technique operates on frequency response measurements, commonly provided by the control card of AMB systems, and therefore do not need for additional sensors or instruments.
Preliminary experiments, carried out on a cold compressor installed in the Large Hadron Collider (LHC) cryogenic system at the European Organization for Nuclear Research (CERN), are presented.

Keywords: Active magnetic bearings, fault detection, noise power estimation

1. INTRODUCTION

At the European Organization for Nuclear Research (CERN), the Large Hadron Collider (LHC) employs high-field superconducting magnets operating in static baths of pressurised superfluid helium below $2.0\,\mathrm{K}$. This low operating temperature is dictated by the high-field operation of the superconducting cable, based on Nb-Ti alloy [1]. To reach this temperature, the most advanced and complex cryogenic technologies are used. As the majority of industries installations, deviations from normal behaviour (faults) may result soon or later in process interruptions (failures), if no counteractions are taken. The difference from conventional industries is that repairing a cryogenic machine and reaching the process nominal conditions could be a time consuming action due to the thermodynamic constraints. For this reason, fault diagnostic functions, capable to detect and identify faults, before their degeneration into failures, become more and more important. In cryogenic installations, the most critical class of equipments consists of rotating machinery, such as pumps, turbines and compressors.
Rotating machinery fault detection techniques have been widely discussed in literature, and the most used approaches exploit wavelet transforms [2–8], and support vector machines [9–11]. These fault detection techniques require machine vibrations or sound measurements. The cold compressors under study are equipped with active magnetic bearings (AMB). In such a system, due to the contact-free rotor support, vibrations and sound levels are not as important as the rotating machinery equipped with different bearing technologies. Furthermore, such a system gives the possibility to perform several measurements in time or frequency domain without additional sensors. In literature, several techniques for fault detection for systems with active magnetic bearing have been proposed. The approach proposed in [12] to detect unbalance faults is based on a signature analysis on excitation currents, but external current sensors to avoid invasive and expensive modifications are needed. To detect rotor cracks, another approach based on signature analysis on system frequency response was proposed in [13, 14]. The AMB was used to excite the rotor with a harmonic force at an appropriate frequency. The frequency response presented a specific signature that was used to detect cracks in the rotor. Finally, a model-based approach was proposed by [15]. A finite element modelling technique was used and a consequent high computational effort was required.
In this paper, a fault detection technique to be integrated in the cryogenic compressors maintenance is proposed. The idea is to evaluate the overall mechanical quality, through the deviations of a chosen quality index. In particular, the proposed fault detection technique consists of three phases. In a former phase, a nominal condition is identified by the Frequency Response Function (FRF) measured on a refernce AMB system, then, the noise power on this nominal record is assessed together with its standard deviation. At a later stage, the FRF of the system under test is measured and it is compared with the nominal record of the reference system, by means of a significance test. This technique is conceived not only to compare the compressor mechanical quality with a reference one, but also to check the mechanical behaviour of the same compressor over a long time horizon.
The paper is organized as it follows: in Section 2, the compressor system used in this work is briefly recalled, then, in Section 3, the proposed fault detection technique is described. Finally, in Section 4, some preliminary experimental tests are presented, where the proposed fault detection technique has been applied to a cold compressor of the LHC.

2. THE COLD COMPRESSOR SYSTEM

The $1.9\,\mathrm{K}$ superfluid helium baths for the superconducting magnets of the LHC are provided by

8 refrigeration units of 2.4 kW by IHI-Linde and Air Liquide [16]. During the normal operations of the LHC, the IHI-Linde system presented some problems in terms of reliability. In particular, the cold compressors were identified as the cause of several process interruptions. For this reason, this paper is devoted to the fault detection for cold compressors installed in the refrigeration unit by IHI-Linde, but the proposed technique, due to its general purpose nature, can be also applied to the Air Liquide system.
The IHI-Linde refrigeration unit is composed by (Fig.1)[17] (i) a warm compression station (WCpS), including an oil lubricated screw compressor (WCp), with the associated oil removal system (ORS); (ii) a cold compressor box (CCB), including mainly a train of cold compressors (CC1-4), 2 heat exchangers (Hx1-2), a phase separator (Ph. Sep.), and 2 turboexpanders (Tu1-2); (iii) the interfaces with the LHC (header B);(iv) and a 4.5 K refrigerator connections (headers C and D).
Most critical devices in the refrigeration unit are: (i) in the warm compression station, the oil removal system, and (ii) in the cold compressor box, the cryogenic turbines Tu1-2 and the compressors CC1-4. All the possible traces of oil, up to a residual of few ppb, are removed in the oil removal system before sending the compressed helium to the cold compressor box. This particular oil (Breox) is used in the screw compressor (WCp) to increase the tightness of the entire process. Particular attention must be paid also to the cryogenic turbines, because they cannot correctly run in presence of impurities in the helium flow (Breox, water or nitrogen). The cold compressors installed in the box are critical because of their mechatronic nature, in fact they rely on active magnetic bearings for shaft levitation.
A generic compressor with active magnetic bearing (Fig.2) is composed by [18]: position and speed sensors; a controller unit necessary to stabilize the suspense state of the rotor; power amplifiers; actuators (radial and axial bearings) responsible for rotor levitation, and, finally, the mechanical compressor.

In this particular case, the AMB, included in IHI-LINDE Cold Compressor System, has two radial bearings and one axial bearing; 2 pulse sensors; 10 position sensors;

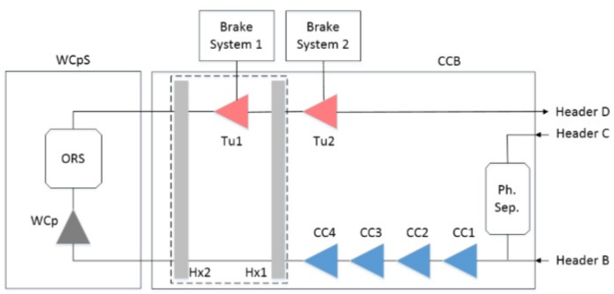

Figure 1. 1.8 K refrigeration unit architecture.

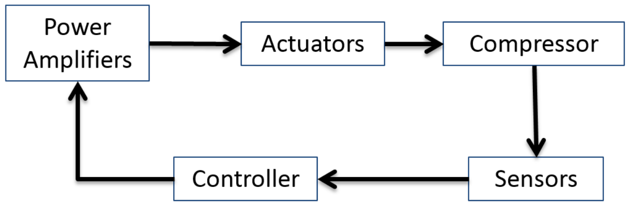

Figure 2. Active magnetic bearing system architecture.

10 power amplifiers and a controller board. The power amplifiers and the controller board are included in one external module provided by MECOS. To control the rotational speed, a three-phases induction motor, together with a variable frequency driver, is used. In active magnetic bearings systems, several signals are directly available from the controller unit without additional devices or sensors. The measurements can be divided in time-domain (shaft position and bearing excitation current) and frequency-domain measurements (controller sensitivity and the FRF). The proposed fault detection technique is based on the FRF measurements.

3. PROPOSED FAULT DETECTION TECHNIQUE

Basic Idea

The basic idea underlying the proposed fault detection technique is to identify a parametric model of a reference system, representing the non-faulty case. Then, the noise power of the system under test is assessed, too, and compared with that obtained in reference conditions. A significance test is finally applied to decide if a fault has occurred.
In the next subsections, details about the two phases of identification and fault detection will be described.

Model identification

Many transfer-function models are available [19]. In this paper, a scalar matrix-fraction description, better known as a common-denominator model, will be considered. The relationship between output ($o = 1, ..., N_o$) and input ($i = 1, ..., N_i$) can be modelled in the frequency domain as:

$$\hat{H}_k(\Omega_f, \theta) = \frac{N_k(\Omega_f, \theta)}{d(\Omega_f, \theta)} \tag{1}$$

at frequency f ($f = 1, ..., N_f$) and with k the output/input combination ($k = 1, ..., N_o N_i$), $N_k(\Omega_f, \theta)$ the numerator polynomial and $d(\Omega_f, \theta)$ the common-denominator polynomial defined by:

$$N_k(\Omega_f, \theta) = \sum_{j=0}^{n} N_{kj}\Omega_f^j; \quad d(\Omega_f, \theta) = \sum_{j=0}^{n} d_j \Omega_f^j \tag{2}$$

In this paper, a discrete-time domain model is considered and Ω_f^j is given by $\Omega_f^j = e^{(-i\omega_f T s)}$, where T_s is the sampling period. The coefficients N_{kj} and d_j are the parameters to be estimated and they are grouped together in one parameter vector θ.

In general, the polynomial order n of the denominator and numerator can differ. The linearized (weighted) Least-Squares (LS) equation error ε_k is obtained by replacing in (1) the model $\hat{H}_k$ by the measured frequency response functions H_k and multiplying with the denominator polynomial d:

$$\varepsilon_k(\omega_f, \theta) = W_k(\omega_f) N_k(\Omega_f, \theta) - H_k(\omega_f) d(\Omega_f, \theta) \approx 0 \tag{3}$$

where, $W_k(\omega_f)$ is a frequency-dependent weighting function which can be used to improve the estimator.
As (3) is linear-in-the-parameters and in the Fourier data, it can be reformulated as $\mathbf{J}\theta \approx \mathbf{0}$:

$$\varepsilon = \mathbf{J}\theta = \begin{bmatrix} \mathbf{\Gamma_1} & 0 & \cdots & 0 & \mathbf{\Phi_1} \\ 0 & \mathbf{\Gamma_2} & \cdots & 0 & \mathbf{\Phi_2} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \mathbf{\Gamma_{N_o}} & \mathbf{\Phi_{N_o}} \end{bmatrix} \begin{bmatrix} \theta_{\mathbf{n_1}} \\ \theta_{\mathbf{n_2}} \\ \vdots \\ \theta_{\mathbf{n_{N_o}}} \\ \theta_{\mathbf{d}} \end{bmatrix} \approx 0 \tag{4}$$

with

$$\mathbf{\Gamma_k} = \begin{bmatrix} \mathbf{\Gamma_k}(\omega_1) \\ \mathbf{\Gamma_k}(\omega_2) \\ \vdots \\ \mathbf{\Gamma_k}(\omega_{N_f}) \end{bmatrix}, \quad \mathbf{\Phi_k} = \begin{bmatrix} \mathbf{\Phi_k}(\omega_1) \\ \mathbf{\Phi_k}(\omega_2) \\ \vdots \\ \mathbf{\Phi_k}(\omega_{N_f}) \end{bmatrix}, \tag{5}$$

$$\theta_{\mathbf{N_k}} = \begin{bmatrix} N_{k,0} \\ N_{k,1} \\ \vdots \\ N_{k,n} \end{bmatrix}, \quad \theta_{\mathbf{d}} = \begin{bmatrix} d_0 \\ d_1 \\ \vdots \\ d_n \end{bmatrix}. \tag{6}$$

and

$$\mathbf{\Gamma_k}(\omega_f) = W_k(\omega_f)[\Omega_f^0, \Omega_f^1, ..., \Omega_f^n] \tag{7}$$

$$\mathbf{\Phi_k}(\omega_f) = -\mathbf{\Gamma_k}(\omega_f) H_k(\omega_f) \tag{8}$$

It should be noted that the Jacobian matrix $\boldsymbol{J}$ is independent on the parameter $\boldsymbol{\theta}$ to be estimated, as (3) is linear-in-the-parameters. Therefore, the size of $\boldsymbol{J}$ can be reduced by formulating the normal equations:

$$\mathbf{J^H J}\theta = \begin{bmatrix} \mathbf{R_1} & \cdots & 0 & \mathbf{S_1} \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & \mathbf{R_{N_o N_i}} & \mathbf{S_{N_o N_i}} \\ \mathbf{S_1^H} & \cdots & \mathbf{S_{N_o N_i}^H} & \sum_{k=1}^{N_o N_i} \mathbf{T_k} \end{bmatrix} \theta \approx \mathbf{0} \tag{9}$$

with $\mathbf{R_k} = \mathbf{\Gamma_k^H \Gamma_k}$, $\mathbf{S_k} = \mathbf{\Gamma_k^H \Phi_k}$ and $\mathbf{T_k} = \mathbf{\Phi_k^H \Phi_k}$.
If the discrete-time domain formulation is used, these matrices have a Toeplitz structure and can be constructed in a fast way. Elimination of the numerator coefficients from (9) by substitution of

$$\theta_{\mathbf{N_k}} = \mathbf{R_k^{-1} S_k} \theta_{\mathbf{d}} \tag{10}$$

results in the so-called reduced normal equations:

$$\left[\sum_{k=1}^{N_o N_i} (\mathbf{T_k} - \mathbf{S_k^H R_k^{-1} S_k}) \right] \theta_{\mathbf{d}} = \mathbf{M}\theta_{\mathbf{d}} \approx 0 \tag{11}$$

It has been proven in [20] that the LS or TLS solutions for $\theta_{\mathbf{d}}$ obtained by solving the compact problem (11) are the same as obtained by solving the full problem (9) with the same constraint. Once the denominator coefficients are determined, back substitution in (10) is used to derive the numerator coefficients.

Fault detection technique

Once the model has been obtained, a record, representing the nominal behavior cleaned of the noise, can be obtained from (1), where the coefficients of the numerator and the denominator, obtained from (10) and (11), have been substituted.

Let the identified record be called the nominal record. The nominal condition is characterized by estimating the noise power σ_w^2 from the acquired record, and its variation, due to the noise overlapped on the record. In a latter phase, the presence of a fault on the system is detected by acquiring a new record and and comparing it versus the nominal record. A fault will be detected if the measured σ_w^2 is higher than the noise power limit defined by the nominal σ_w^2 value plus two times its standard deviation.

Assuming that the acquired record is corrupted by white Gaussian noise, with variance σ_w^2, and that the variance of the remaining noise on the record, filtered by the model application is much lower than that of the noise on the original record, an estimate of the noise power can be obtained from the residuals:

$$\mathbf{r} = \mathbf{h} - \hat{\mathbf{h}} \tag{12}$$

In particular, indicating with $\bar{P}_r$ the mean squared value of $\mathbf{r}$:

$$\bar{P}_r = \frac{1}{N} \sum_{i=1}^{N} r_i, \tag{13}$$

it can be shown that $\bar{P}_r N / \sigma_w^2$ is chi–squared distributed with N degrees of freedom. Therefore, taking the mean value leads to:

$$E\left\{ \frac{\bar{P}_r N}{\sigma_w^2} \right\} = N. \tag{14}$$

An estimate of σ_w^2 is then obtained directly evaluating $\bar{P}_r$:

$$\hat{\sigma}_w^2 = \bar{P}_r \tag{15}$$

Taking the variance of $\bar{P}_r N / \sigma_w^2$ leads to:

$$Var\left\{ \frac{\bar{P}_r N}{\sigma_w^2} \right\} = 2N, \tag{16}$$

and:

$$Var\left\{ \bar{P}_r \right\} = Var\left\{ \hat{\sigma}_w^2 \right\} = \frac{2}{N} \sigma_w^4. \tag{17}$$

The σ_w^2 standard deviation can be finally calculated and the nominal noise power limit can be set.

4. EXPERIMENTAL ANALYSIS ON A COLD COMPRESSOR

The proposed fault detection technique has been tested on the LHC refrigeration unit described in section 2. In particular, all the measurements refer to the first stage compressor (CC1).

Diagnostics problem

The proposed method will allow, during the LHC ordinary maintenance stops, to evaluate the mechanical quality of the cold compressors through a proactive fault detection. Thanks to the nature of the active magnetic bearings, the system FRF $H = Y/X$ can be measured without additional sensors or measurement devices (Fig. 3). In particular, the system outputs Y are the rotor position measurements, while the inputs X are the sum of the controller signals (X') and an excitation signal X_0. A FRF measurements on a reference compressor is required to identify the nominal noise power with the relative standard deviation.

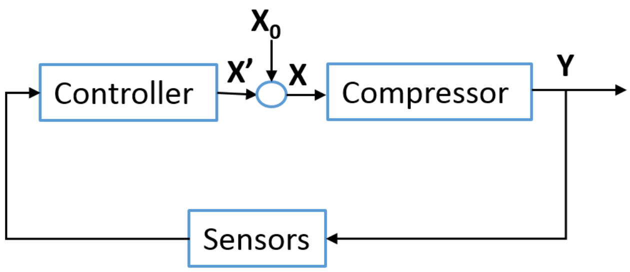

Figure 3. Measurement system architecture.

Proof-of-principle scenario

To check the correct operation of the cryogenic system after the LHC Long-Shutdown 1 (LS1) some tests on the IHI-Linde refrigerator unit, in different process conditions, were performed. For a fixed rotational speed, the cold compressors transfer functions were measured. The measurements were performed for two different process temperatures: at ambient temperature ($\sim$300 K) and at 30 K. The compressors test rotational speeds during the measurements are: 15 Hz for compressor stage 1, 20 Hz for compressor stage 2, 30 Hz for compressor stage 3 and 40 Hz for compressor stage 4.

Experimental Results

For the fault detection method validation, first the system identification in the non-faulty case was carried out. The compressor stage 1 was chosen as system under test. In Fig. 4, the identified model and the measured FRF are shown.

After several tests, an optimal polynomial order was found, and the good agreement between the identified model and the measurement of the entire system emphasizes that

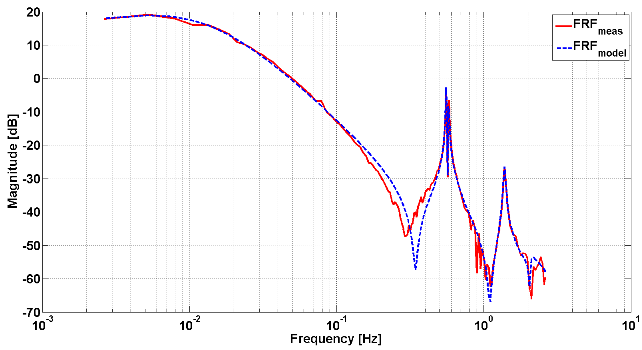

Figure 4. Identification of the nominal condition.

the identification technique can be extremely helpful in detecting faulty states.

Consequently, the noise power and its standard deviation were calculated from measurement residuals and they were used as a reference for the fault detection, as described in 3. The reference noise power and its variance are $\sigma^2_{w_{ref}} = 0.0109$ and $Var\{\sigma^2_{w_{ref}}\} = 1.49 \cdot 10^{-6}$, respectively. Therefore, the confidence limit used for the fault detection is:

$$\tau = \sigma^2_{w_{ref}} + 2\sqrt{Var\{\sigma^2_{w_{ref}}\}} = 0.0133. \qquad (18)$$

A second compressor stage 1 was then considered as system under test and a FRF measurement was performed. In Fig.5 the new FRF and the previously modelled system are shown. As it is possible to see, the new σ^2_w value is definitely higher than the nominal condition limit.

The new σ^2_w was then calculated:

$$\sigma^2_w = 44.4336 \qquad (19)$$

Thanks to the proposed technique, a fault was then detected, and the faulty compressor was sent back to manufacturer. The IHI-LINDE company confirmed that some minor mechanical problems were found.

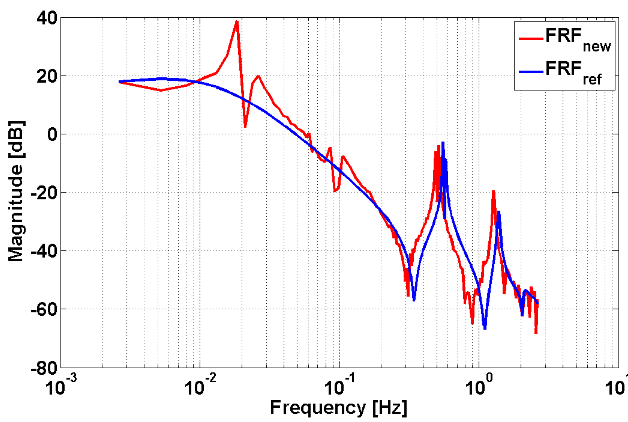

Figure 5. Comparison between reference record (blue) and acquired record (red).

5. CONCLUSIONS

In this paper, a fault detection technique for cryogenic cold compressors based on active magnetic bearings has been presented. The proposed technique takes as input the frequency domain record taken from the control card of the AMB system, thus it does not need of additional sensors or instruments. The proposed technique has been applied to some cold compressors installed on the CERN LHC and it was able to detect a fault that has been then confirmed by further analysis. Further work is directed to improve the fault detection technique such to provide additional information about the type of fault that has occurred.

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