Health Monitoring of a Pneumatic Valve Using a PIT Based Technique

João P. P. Gomes[1], Bruno C. Ferreira[1], Dennis Cabral[1], Roberto K. H. Glavão[2] and Takashi Yoneyama[2]

[1] *EMBRAER – Empresa Brasileira de Aeronáutica, S.J. dos Campos, SP, 12227901,Brazil*
joao.pordeus@embraer.com.br
bruno.carneiro@ embraer.com.br
dennis.cabral@ embraer.com.br

[2] *ITA – Instituto Tecnológico de Aeronáutica, S. J. dos Campos, SP, 12228900, Brazil*
kawakami@ita.br
takashi@ita.br

ABSTRACT

This paper is concerned with the development of a health monitoring system for a pneumatic valve employed in pressure regulation systems. The proposed method is based on the statistical analysis of deviations of the controlled pressure signal from a baseline behavior. For this purpose, the Probability Integral Transform is employed to calculate an index of dissimilarity between the distributions of monitored and baseline data. The proposed method was applied to field records of 15 units, which were monitored during eight months. In the case of failed units, the degradation index showed an increasing trend prior to the failure occurrence. It is worth noting that the failure level was similar in all cases, which is an important characteristic for the future development of prognostic solutions. In addition, no false alarms were observed for the healthy units. The results found in the case study are realistic and fit within practical requirements to support maintenance decision*

1 INTRODUCTION

Health monitoring has been rapidly evolving in the latest years and many different applications of this technology are being pursued for industrial and vehicle components and systems. Many benefits can potentially be provided by such kind of technologies, such as the reduction of maintenance costs and increase in safety. Applications on health monitoring techniques involve many types of systems such as pneumatic (Demetgul *et al*, 2009), hydraulic (Byington *et al*, 2007) and electronic (Kalgren *et al*, 2007).

This paper presents a health monitoring methodology for a pneumatic valve in a pressure control system. The proposed method is based on the statistical analysis of the controlled pressure signal, which deviates from normal behavior in the presence of valve degradation. For this purpose, the Probability Integral Transform (Ihida, 2005), (Chen et al, 2007), (Leão et al, 2010) is employed to quantify alterations of the probability distribution of the measured data with respect to a reference distribution. The proposed methodology differs from classical methods like the Statistical Probability Ratio Test (SPRT) proposed by (Wald A., 1945) because it estimates only the distribution of the normal data, working as a novelty detection algorithm.

The paper is organized as follows. Section 2 describes the pressure control system under consideration. Section 3 presents the proposed health monitoring technique. Results for actual field data are discussed in Section 4. Finally, concluding remarks are given in Section 5.

2 SYSTEM DESCRIPTION

The pressure control system consists of a pneumatic actuated valve, a torque motor, a pressure transducer and a torque motor controller. Its purpose is to keep the downstream pressure at a controlled set point value.

A pneumatic actuator controlled by a torque motor servo pressure signal provided by a remotely located controller drives the valve flap. Duct pressure is ported directly to the supply area of the actuator piston. This pressure force, along with the actuator spring force, provides the closing force for the butterfly disc. The opening force is provided by the torque motor servo pressure acting on the larger portion of the actuator piston. Servo pressure is controlled remotely by a controller output current generated from the difference between the set point and the measured downstream pressure at the pressure transducer. If the servo pressure is low, the valve remains closed. As the servo pressure increases, the opening force increases, until the point where the net opening force exceeds the combined closing force, which causes the valve to open. A connecting link translates the axial motion of the actuator piston into rotational motion of the valve flap.

The valve will regulate downstream pressure until the servo pressure increases to fully open the valve. Figure 1 shows an overview of the system described above.

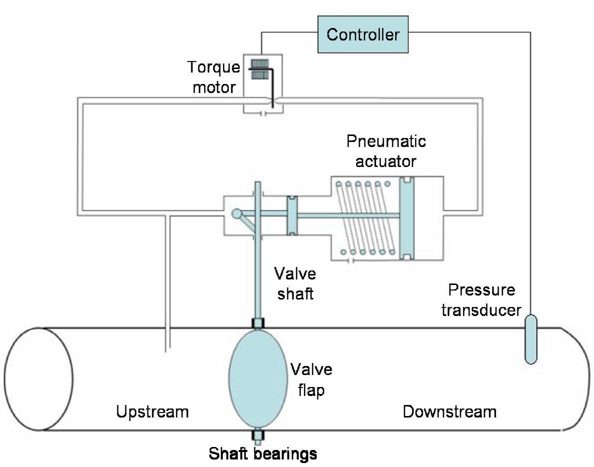

Figure 1: Pressure control system.

The most common failure modes on this system are related to the pneumatic valve itself. Examples include friction increase due to shaft bearings degradation, spring ageing and internal chamber leakages due to seal degradation. Over the last five years of operation, maintenance teams have reported a large number of failures in this pressure control system, mostly related to the pneumatic valve. Such reports motivated the development of the health monitoring solution presented in this paper.

3 HEALTH MONITORING METHODOLOGY

Field observations indicate that downstream pressure signals exhibit a slight increase in amplitude before an event of failure. This deviation from nominal behavior is illustrated in Figure 2. The left plot presents the pressure signal of a normal system, whereas the right plot shows the pressure signal a few days before a failure.

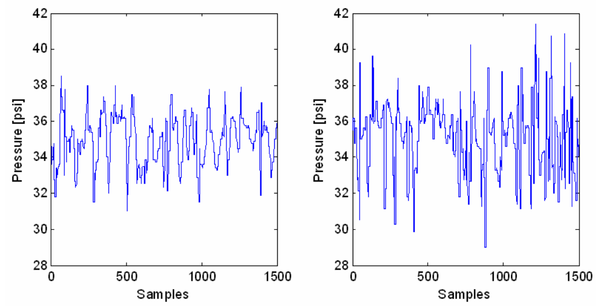

Figure 2: Pressure signal of a normal (left) and a degraded valve (right).

The change in the pressure signal can be characterized in a more appropriate manner by using histogram representations, as shown in Figure 3. As can be seen, the pressured data from the degraded system exhibit a distribution with a longer tail, as compared to the distribution for the new (non-degraded) system.

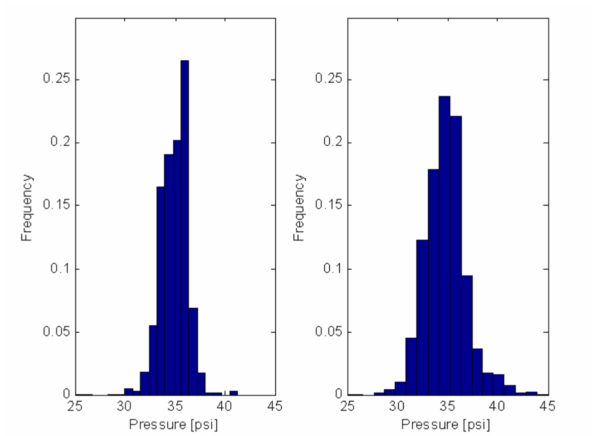

Figure 3: Histograms for the pressure signals presented in Figure 2.

Such a difference between distributions motivated the health monitoring methodology proposed in this work. The main idea consists of creating a metric for the dissimilarity between the distributions of a baseline dataset and the dataset generated by the monitored system. For this purpose, a method based on the Probability Integral Transform (PIT) was developed.

The proposed method estimates the distribution of the data in a non-parametric manner and computes an index of dissimilarity between a baseline dataset and the monitored data.

3.1 Probability Integral Transform

Given a probability space $\{\Omega, F, P\}$ and a random variable X: $\Omega \rightarrow \Re$, the cumulative distribution function (CDF) of X is defined as

$$F(x) = P(\{\omega \in \Omega \mid X(\omega) \leq x\}),\ x \in \Re \tag{1}$$

Assuming that $F(.)$ is continuous, a new random variable Z can be defined by using X as the input for the CDF function $F(.)$:

$$Z = F(X) \tag{2}$$

This new random variable is uniformly distributed over the range (0,1). Figure 4 illustrates such transformation.

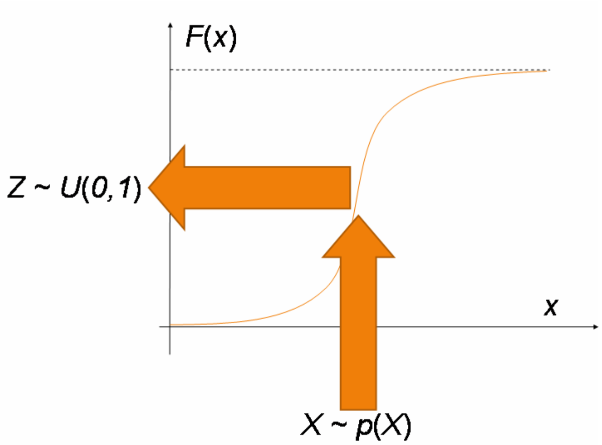

Figure 4: Obtaining random variable Z using PIT.

3.2 Using PIT for Health Monitoring

The transformation of a given random variable into a random variable with uniform distribution has many applications. Examples can be found in econometrics (Ihida, 2005), state estimation (Chen *et al*, 2007) and failure prognostics (Leão *et al*, 2010). In the present work, PIT is used for health monitoring. The proposed procedure can be described by the following steps:

1. Calculate an empirical CDF using measured values of the monitored variable under baseline (i.e. non-degraded) operating conditions.
2. Define $F(\cdot)$ according to equation (1) using the CDF calculated in step 1.
3. Apply $F(\cdot)$ to every new measurement of the monitored variable.
4. Evaluate the resulting distribution by comparison to an ideal distribution $U(0,1)$.

In this work, two approaches for performing step 4 are proposed, a graphical and a quantitative approach. Both are based on the works of (Chen *et al*, 2007) and (Leão *et al*, 2010). The first approach is based on the empirical CDF of the transformed variable. If the data under analysis have the same distribution of the baseline data used to generate function $F(\cdot)$, the CDF of the transformed variable should be similar to the CDF of a $U(0,1)$ distribution, as illustrated in Figure 5.

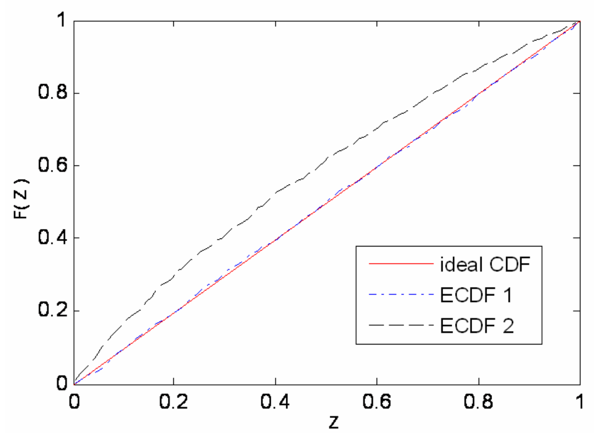

Figure 5: Graphical representation of the PIT-based evaluation.

In Figure 5 the "ideal CDF" line represents a $U(0,1)$ distribution. The curve "ECDF 1" is an example of a empirical CDF resulting from a set of data with the same distribution of the data used to generate the function $F(\cdot)$. The curve "ECDF 2" is an example of a empirical CDF resulting from a set of data with a distribution that is different from the distribution of the data used to generate $F(\cdot)$.

The quantitative approach consists of calculating the following measure of dissimilarity from the CDF plot, as proposed by (Leão *et al*, 2010):

$$B = \frac{1}{m}\sum_{j=1}^{m}\left|P_e(y_j) - y_j\right| \tag{3}$$

where m is the number of points used to construct the discrete empirical CDF, y_j is the value assumed by each of these points in a CDF $U(0,1)$ and $P_e(\cdot)$ is the empirical CDF value. The resulting B-index was termed "Badness Indicator" in (Leão *et al*, 2010). In the present work, the B-index will be intepreted as an indicator of degradation.

4 RESULTS

The proposed health monitoring method was applied to actual field data of the pressure regulation system, according to steps 1 – 4 described in the previous section.

In steps 1 and 2, a baseline record containing 17500 pressure data points was acquired. The empirical CDF of these data were used to define $F(\cdot)$.

Steps 3 and 4 comprise the evaluation of the system condition over time. For this purpose, a set of 15 units of the system were monitored during eight months. The *B* index was calculated for each new data record acquired during this period.

During the monitoring period, three failure occurrences were reported by the maintenance team. A detailed inspection indicated that such failures were caused by the pneumatic valve.

Figure 6 presents the *B*-index obtained for one of the pressure regulation systems that did not fail during the monitoring period. As can be seen, the time series of

B-index values does not exhibit a trend that could be interpreted as an increase in degradation. Such a finding is consistent with the fact that no failures were reported in this period. Similar results were obtained for the other monitored units that remained operational throughout the monitoring period.

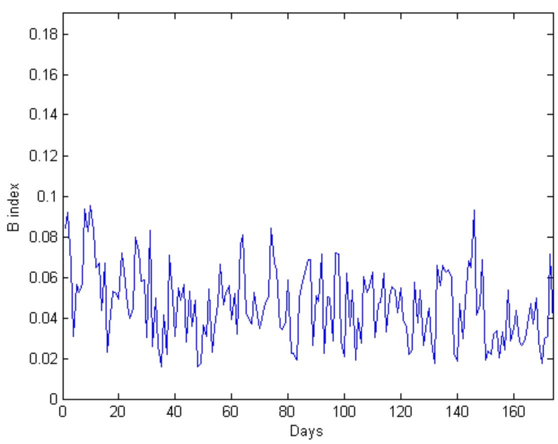

Figure 6: *B*-index for a system that did not fail during the monitoring period.

Figure 7, Figure 8 and Figure 9 present the *B*-index values for the units that did fail. As can be seen, these figures a clear trend of increasing degradation prior to the failure. It is also important to notice that all three failures occurred when the *B*-index was at a similar level. These are desired characteristics when establishing a threshold for component removal or even in the development of prognostic solutions.

After the maintenance actions, it is possible to see an abrupt reduction in the *B*-index level for each unit. The level reached is similar to those of the units without degradation.

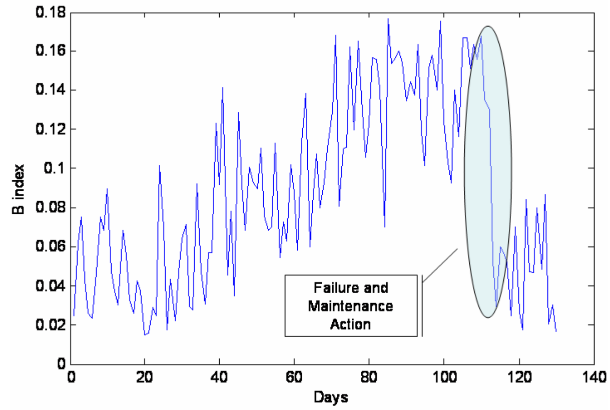

Figure 7: *B*-index for the monitored system near a failure occurrence (occurrence 1)

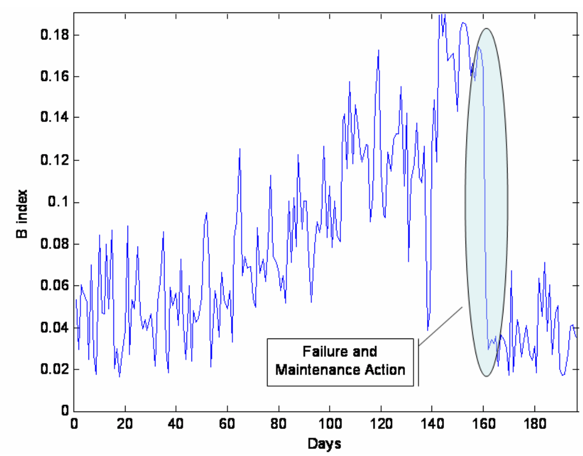

Figure 8: *B*-index for the monitored system near a failure occurrence (occurrence 2).

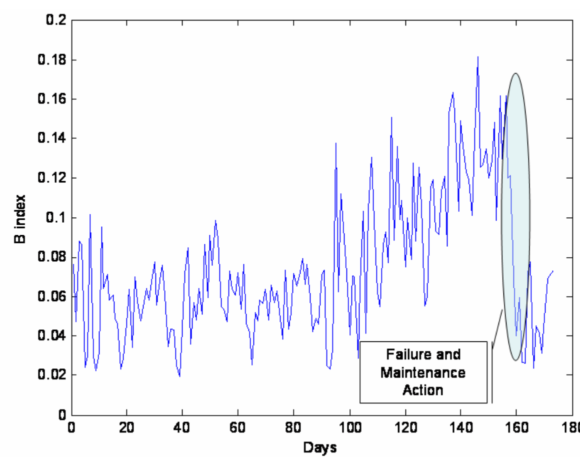

Figure 9: *B*-index for the monitored system near a failure occurrence (occurrence 3).

5 CONCLUSION

This paper presented a methodology of health monitoring for a pneumatic valve in a pressure control system by analyzing the regulated pressure behavior.

The proposed health index was capable to identify an increasing degradation that lead to failure occurrences. No health index increasing behavior was observed for healthy units.

In the case of failed units, the degradation index showed an increasing behavior until a critical level, which was similar for all failure occurrences. These are very important characteristics in the development of prognostic solutions. The results found in this case study are realistic and fit within practical requirements to support maintenance decision.

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REFERENCES

(Byington *et al*, 2003) C. S Byington,., M. Watson., D. Edwards., and B. Dunkin. 2003. In-Line Health Monitoring System for Hydraulic Pumps and Motors. *In Proceedings of the IEEE Aerospace Conference*. Big Sky, 2003.

(Chen *et al*, 2007) L. Chen., C. Lee , R. K. Mehra How to Tell a Bad Filter Through Monte Carlo Simulations. *IEEE Transactions on Automatic Control, 52, 1302-1307.*

(Demetgul *et al,* 2009) M. Demetgul, I. N. Tansel, S. Taskin. Fault diagnosis of pneumatic systems with artificial neural network algorithms. *Expert systems with Applications*, 36, 10512-10519.

(Ishida, 2005) I. Ishida. Scanning Multivariate Conditional Densities with Probability Integral Transforms. CIRJE Discussion Paper CIRJE-F-369, Faculty of Economics, University of Tokyo.

(Kalgren *et al*, 2007) P. W. Kalgren, M. Baybutt, A. Ginart, C. Minnella, M. J. Roemer and T. Dabney. Application of Prognostic Health Management in Digital Electronic Systems. *In Proceedings of the IEEE Aerospace Conference*. Big Sky, 2007

(Leão *et al*, 2010) B. P. Leão , J. P. P. Gomes, R. K. H. Galvão, T. Yoneyama. How to Tell the Good from the Bad in Failure Prognostics Methods. *in Proceedings of IEEE Aerospace Conference*, Big Sky, 2010

(Wald, A. 1945) A. Wald. Sequential Tests of Statistical Hypotheses *The Annals of Mathematical Statistics*, Vol16, No 2, pp 117-186

João Paulo P. Gomes holds a bachelor's degree on Electrical Engineering from Universidade Federal do Ceará (UFC, 2004), Brazil, and Master Degree on Aeronautical Engineering (2006) from ITA, São José dos Campos, SP, Brazil. He is with Empresa Brasileira de Aeronáutica S.A (EMBRAER), São José dos Campos, SP, Brazil, since 2006. He works as a Development Engineer of a R&T group at EMBRAER focused on PHM technology applications in aeronautical systems

Bruno C. Ferreira holds a bachelor's degree on Electrical Engineering from Universidade Federal do Rio de Janeiro (UFRJ, 2005), Brazil, and Master Degree on Electrical Engineering (2009) from COPPE/UFRJ , Rio de Janeiro, RJ, Brazil. He is with Empresa Brasileira de Aeronáutica S.A (EMBRAER), São José dos Campos, SP, Brazil, since 2009. He works as a Development Engineer of a R&T group at EMBRAER focused on PHM technology applications in aeronautical systems

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Dennis Cabral holds a bachelor's degree on Electrical Engineering from Universidade de São Paulo (USP, 2004), Brazil, and Master Degree on Aeronautical Engineering (2008) from ITA, São José dos Campos, SP, Brazil. He is with Empresa Brasileira de Aeronáutica S.A (EMBRAER), São José dos Campos, SP, Brazil, since 2006. He works as a Development Engineer of a R&T group at EMBRAER focused on PHM technology applications in aeronautical systems

Roberto Kawakami Harrop Galvão is an Associate Professor of Systems and Control at the Electronic Engineering Department of ITA. He holds a bachelor's degree in Electronic Engineering (Summa cum Laude, 1995) from ITA, Brazil. He also obtained the master's (1997) and doctorate (1999) degrees in Systems and Control from the same institution. Dr. Galvão is a Senior Member of the IEEE and an Associate Member of the Brazilian Academy of Sciences. He has published more than 150 papers in peer-reviewed journals and conference proceedings. His main areas of interest are fault diagnosis and prognosis, wavelet theory and applications, and model predictive control.

Takashi Yoneyama is a Professor of Control Theory with the Electronic Engineering Department of ITA. He received the bachelor's degree in electronic engineering from ITA, Brazil, the M.D. degree in medicine from Universidade de Taubaté, Brazil, and the Ph.D. degree in electrical engineering from the University of London, U.K. (1983). He has more than 250 published papers, has written four books, and has supervised

more than 50 theses. His research is concerned mainly with stochastic optimal control theory. Prof. Yoneyama served as the President of the Brazilian Automatics Society in the period 2004-2006.