Multidimensional Monitoring System of State Machines

Bogdan Zoltowski[1], Leonel F. Castaneda, Mariusz Zoltowski[2], Krzysztof Napieraj, Jacek Wachowicz Wachowicz[3], Ryszard Bielski[4]

[1]*Faculty of Mechanical Engineering, UTP University of Science and Technology in Bydgoszcz, al. prof. S. Kaliskiego 7 85-796 Bydgoszcz, Poland*

[2]*Faculty of Management, UTP University of Science and Technology in Bydgoszcz, al. prof. S. Kaliskiego 7 85-796 Bydgoszcz, Poland*

[3]*BOLS Institute, WSB University in Gdańsk, al. Grunwaldzka 238A, 80-266 Gdańsk, Poland*

[4]*Faculty of Management and Economics, Gdańsk University of Technology, ul. Traugutta 79, 80-233 Gdańsk, Poland*

bogzol@utp.edu.pl, mariusz.zoltowski@utp.edu.pl, jacek_wachowicz@o2.pl, ryszard.bielski@zie.pg.gda.pl

Keywords: Diagnostics, Monitoring, System of Exploitation, Reliability, Damages

Abstract: Technical systems are more complex every day as their electronics and mechanics. Technological advances tend to be autonomous in its performance and perform an auto-diagnosis that allows determining an abnormality existence in a component or subsystem and deciding if the system has to be stopped or not. The conventional maintenance does not allow an integrated diagnosis analysis of a system. Among the factors, that generated condition can be found a lack of communication between units: bad information of management, ignoring relevant of information, a lack of a clear monitoring policy and variables measurement tendency.

1 INTRODUCTION

Technical systems are becoming more complex when talking about their mechanic, and electronic. Technological advances tend to be more auto sufficient, and able to auto diagnose themselves, what allow to determine if any anomaly is present in any subsystem, or component, to finally decide whether the system must or not be stopped (Bongers 2004, Cempel 1999, Formenti et al. 1986, International union of railways 2003, National Instruments 2004).

The conventional maintenance with some factors such as the lack of communication between dependencies, a not proper management of information, not having a clear monitoring policy nor variables trends among other, don't not allow the performance of an integrated diagnose of the system (Natke et al. 2001, Potter et al., 1984, Żółtowski et al. 2006a, Żółtowski et al. 2006b, Żółtowski et al. 2007b, Żółtowski et al. 2007c) .

Due to the previous factors, it is necessary to implement new methodologies of technical diagnostic, in order to satisfy all of the company's needs, getting as result, an integrated diagnose through computing simulation, tools, analysis methods and information evaluation from the machine's technical state (Cempel 1999, Natke 1997, Żółtowski 2007a, Żółtowski 2011).

The energy processors theory is based on a main energy flow analysis, where a system balance arises between input energy N_i, dissipated energy N_d and useful energy N_u (Cempel 2003, Natke 1997).

Through a residual process series as vibration, noise and heat the input energy is dissipated in one of these phenomena, that reflect the technical system wear (accumulated dissipated energy), therefore the dissipated energy study through the system provides inference about the artefacts wear and therefore determining the system technical condition is of interest. Figure 1 shows the methodology followed by the mini-central technical diagnosis. This process involved the next diagnosis stages (Richardson 1995, Tournay 2001, Żółtowski 2006c, Żółtowski 2011):

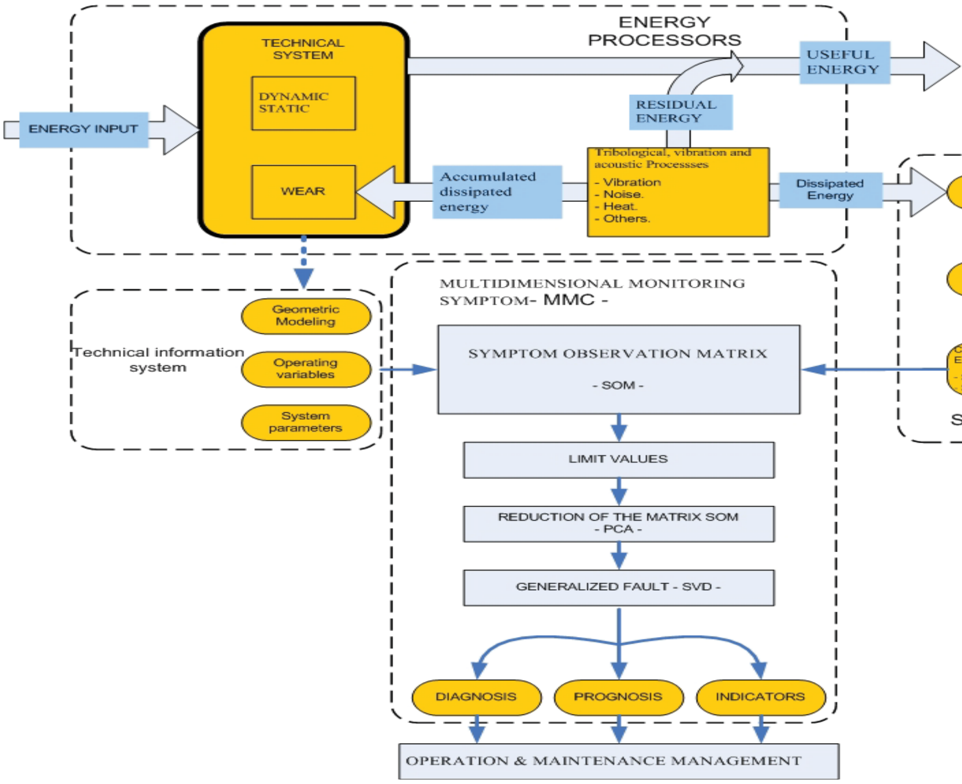

Figure 1: Technical diagnosis methodology for a water turbine .

- Register and acquisition of residual energy (reception and selection points of vibration signals and operation variables).
- Signal processing.
- Statehood monitoring of Francis turbine.
- Multidimensional Monitoring Condition.
- Maintenance ratios establishment.

2 STUDY CASE

As study case for presented methodology is La Herradura's Mini-central Hydroelectric property of Empresas Públicas de Medellín, which is located in the municipality of Frontino, north-east of Medellín, Antioquia. The Mini-central has two water type turbines of horizontal axis, each one with a rated power of 10.4MW and a $5m^3/s$ flow, with a rotation speed of 900rpm and a design net jump of 230.6m. Figure 2 shows up a general scheme of parts forming the turbine.

The Mini-central has two systems able to obtain information of technical condition. The first one is the vibration monitoring system and the second one - is the Mini-central monitoring and control system. The permanent vibration monitoring system for the generator is based on an instrument with the serial number "VDR-24" (Vibro Diagnostics Recorder – 24 channels), in the VDM data module and in the "ATLANT" diagnosis program. The vibrations measurement chain is showed on Figure 3.

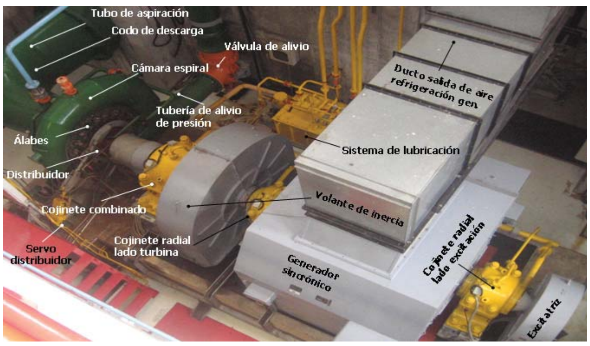

Figure 2: The view of the studied water turbine.

Through this system the r.m.s signals vibration value is monitored (speed and displacement) in points presented on Figure 4.
The system used to central monitoring and control from operation station is the V7 Monitor Pro from Schneider Electric (Figure 5), this allows the data acquisition, monitoring and real time control and has a setting Server-Client and an unlimited number of TAG's (variables).

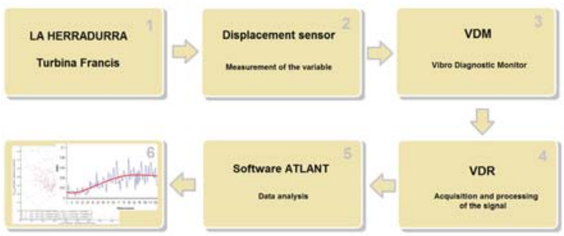

Figure 3: Measurement chain of vibration analysis system.

[symbols: 1) La Herradura's Mini-central. 2) Sensors – Variable Measurement. 3) VDM – Data Module. 4) VDR – Processing and signal acquisition.. 5) ATLANT Software. 6) ATLANT signal and analysis transformation]

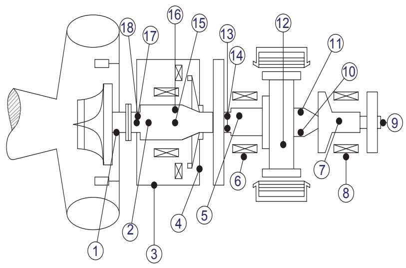

Figure 4: Acquisition point scheme of variables related to vibration.

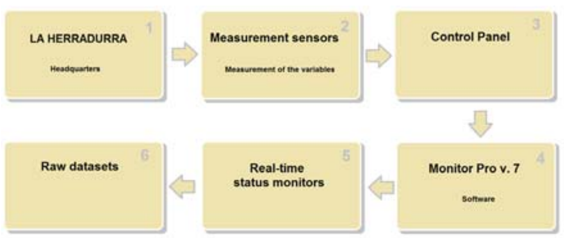

Figure 5: Measurement chain of the monitoring and control system.

[symbols: 1) La Herradura Mini-central. 2) Variables measurement sensors (Pressure, temperature, current, voltage). 3) Control panel. 4) V7 Monitor Pro Software. 5) General deployments of generation and monitoring units. 6) Historical board and reports]

3 MEASUREMENT POINTS SELECTION

Based on measurement points algorithm the mechanical vibration signal is analyzed, received from the three hydro-dynamical bearings based on independence criterion and information quantity. Fort the first case the information independence will be given by inverse area under the curve of coherence $\gamma_{xy}^{2}(f)$ between two signals measured at the same place, for the current study the signals are taken from vertical and horizontal speed in every bearing therefore, there will be a greater information independence when the maximum area, according to the next expression [5]:

$$AC_{xy} = \frac{1}{\int_{0}^{F} \gamma_{xy}^{2}(f)\, dF}$$

To determine the information quantity the coherence values are taken between signals depending on certain frequencies (system characteristic frequencies) and a criterion under the following expression [5]:

AC_{xy} and In_{xy} values are registered in a data base, given the data volume to analyse, an optimization problem is set out, which aims to determine the generation bearing in which the independence and information quantity are the highest.

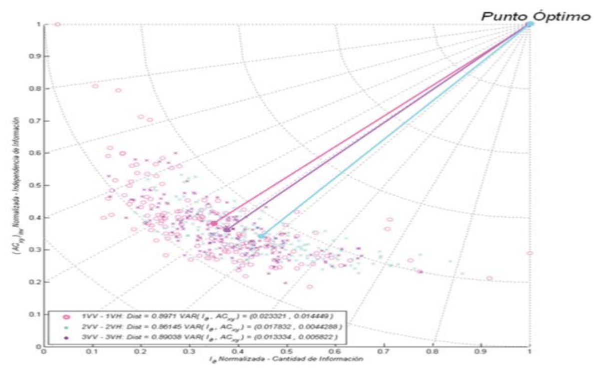

Figure 6: Reception point analysis from diagnosis signal.

According to Figure 6, the reception points of diagnosis signal are located almost at the same distance from the optimal point. This means that has reliable information for the technical diagnosis of the generation unit.

4 SYMPTOMS CALCULATION

During the diagnosis model implementation, a series of new symptoms were calculated to make a follow up of registered signals by the vibration monitoring system, Figure 7 shows up an example of the Amp. Espectro (225Hz):2VV symptom: this refers to the vibration speed amplitude of impeller blades frequency flow (225Hz), in vertical direction of 2 bearing. A data tendency was observed during monitoring time, which indicates the evidence of a system abnormality, thus the evidence the real system statehood condition, allows detecting, locating and evaluating failures in the system. On (Natke 1997) is showed up the symptom definition and some examples are suggested.

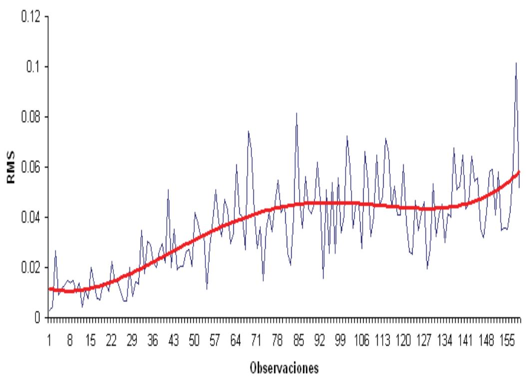

Figure 7: Vibration speed frequency from impeller blades flow (225Hz), in a vertical direction of 2 bearing.

5 OBSERVATION MATRIX ELABORATION

To elaborate the symptom matrix 25 generation and control variables were considered, corresponding to specific average values registered during the monitoring day. This selection was made along with the systems operators, seeking to include the variables that in a certain case can provide abnormality evidence in the system. Regarding to vibration monitoring signals, 210 symptoms were calculated each monitoring day, also based on operators experience and appropriate literature. Among them highlights scalar estimators as: average, RMS value, peak value, peak to peak value, shape factor, standard deviation, bias, among others. In this way a new observation matrix of symptoms will contain 235 variables and 157 observations. The symptoms observation matrix from a system is represented on Figure 8, where columns are different measured symptoms and rows are observations or measurements made for every symptom in different life cycle times of technical system.

6 LIMIT VALUE ESTABLISHMENT FOR ESTIMATORS

Symptoms limit value of diagnosis systems were calculated according to the following relation [5]:

$$S_{\lim} = \bar{S} + \sigma_P \sqrt{\frac{G}{2A}}$$

Where: $\bar{S}$ is the symptom average value during θ machine operation time

$$\begin{array}{ccc} & \text{Sintomas Varaibles} & \\ O_{pr}=\left|S_{ij}\right|= & \begin{bmatrix} S_{1,1} & S_{1,2} & \cdots & S_{1,j} & \cdots & S_{1,r} \\ S_{2,1} & S_{2,2} & \cdots & S_{2,j} & \cdots & S_{2,r} \\ \vdots & \vdots & \ddots & \vdots & & \vdots \\ S_{i,1} & S_{i,2} & \cdots & S_{i,j} & \cdots & S_{i,r} \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ S_{p,1} & S_{p,2} & \cdots & S_{p,j} & \cdots & S_{p,r} \end{bmatrix} & \text{overbracealignl\_} \begin{pmatrix} -\theta_1 \\ -\theta_2 \\ \vdots \\ -\theta_i \\ \vdots \\ -\theta_p \end{pmatrix} \text{Observaciones Mediciones} \\ & i=1,2,\ldots,p & \\ & j=1,2,\ldots,r & \end{array}$$

Figure 8: Symptoms observation matrix.

and the symptom standard deviation, σ_P, A - is the tolerable level of unnecessary established repairs and G is the machine availability.

Figure 9 shows up the relation between the manufacture established limit and the previous calculated method. The set limit observed can be found way above from normal data behaviour therefore do not show variable changes evidence. On the other hand, the calculated limit can identify subtle variable changes being in an historical behaviour range.

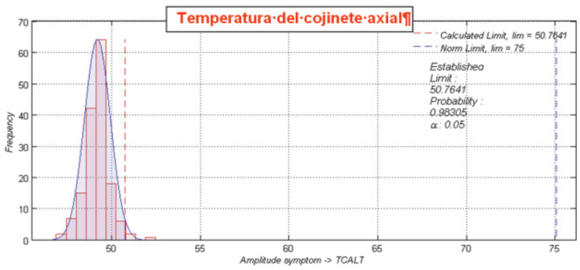

Figure 9: New limit calculation.

6 SINGULAR VALUE DECOMPOSITION

Following the proposed methodology, symptoms observation matrix, its dimensions are reduced through PCA. Then the Singular Vale Decomposition (SVD) is applied with the purpose of extracting different failure modes that evolve in a system, assessing the wear advance used en new indexes and ratios. The SVD application for sizing the symptoms observation matrix can be expressed as follows (Potter 1984):

$$O_{pr} = U_{pp} * \sum_{pr} * V_{rr}^{T}$$

U_{PP} : dimension orthogonal matrix. p, are the left singular vectors. : V_{rr} is an r dimension orthogonal matrix of right singular vectors. : $\sum_{pr}$ is a diagonal matrix of singular values.

The failures profiles are determined using singular values and vectors found with SVD, obtaining a condition evolution interpretation of technical system. These failures are given by (Richardson 1995):

$$SD_t = O_{pr} \times v_t = \sigma_t \cdot u_t$$

Where SD_t is the left singular vector amplified by a respective singular value σ_t. Hence this value leads as bug and information about intensity of failures due to the inclusion of σ_t (Richardson 1995).

The total generalized failure profile $P(\theta)$ or $SumSD$, which represents the general evolution of condition of technical system is determined through (Tournay 2001):

$$P(\theta) = SumSD = \sum_{i=1}^{z} \left| SD_i(\theta) \right|$$

7 IMPLEMENTATION METHODOLOGY

During the implementation methodology at La Herradura's Mini-central an evolving failure on Francis turbine was detected, which is showed up on Figure 10.

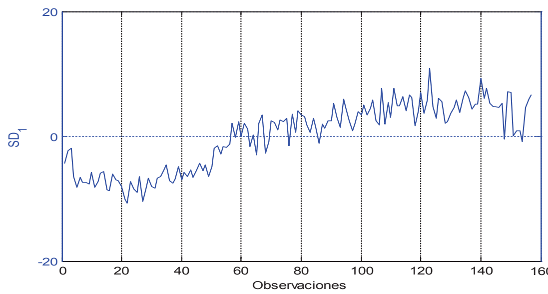

Figure 10: First water turbine failure evolution.

The technical diagnosis showed up that the evolution profile of machine was strongly correlated with variables that describe the technical condition of first Francis turbine bearing. The temperature, the relative axis displacement with respect to combined bearing and the 225 Hz spectral component are part of diagnosis parameters that dominate in this first evaluation unit. The observed frequency corresponds the pitch frequency of blades of the Francis turbine. A continuous component increase was observed during the machine operation time. This occurs as a consequence of interaction between impeller blades and distributor moving blades, a pulse is generated due to the frequency flow pressure of impeller blades (225 Hz, this pulse is labyrinths transported from turbine seals causing an axis push in axial sense, generating a vibration at the same frequency level. With the turbine seals wearing increase, the pulse effect increases, hence, the axial push increases generating vibrations increase.

On Figure 11 the diagnosis parameters tendencies are showed up for Francis turbine operating time related to identify failure.

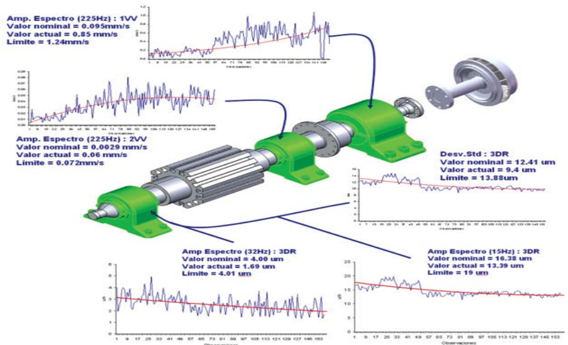

Figure 11: Vibrations evolution related to failure profile.

The probabilistic decision model (Figure 12) and reliability symptoms function (Figure 13) of Francis turbine were determined with important information in any strategy of critical operating systems maintenance. These machine's behaviour patterns allow making correct decisions just in time and reducing risk. It is important to remember the implemented methodology during this project, which is based on real data of Francis turbine condition during utility time.

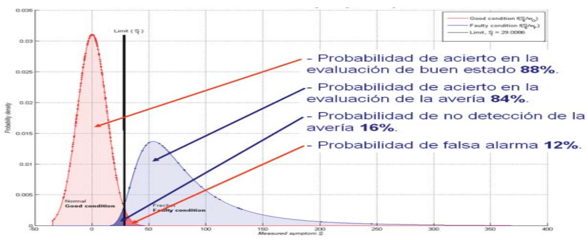

Figure 12: Probabilistic diagnosis model.

8 CONCLUSIONS

Techniques and algorithms used in different branches of science can be applied to technical condition monitoring, as the case of main components analysis and the singular values decomposition.

The multidimensional symptoms monitoring allows identifying changes in the system technical condition and establish possible causes from that condition.

This kind of monitoring in the specific analysed case generate a maintenance decision-making support, which impacts in cost reduction related to maintenance and optimal personal use besides, it generates an increase in the system's availability and reliability.

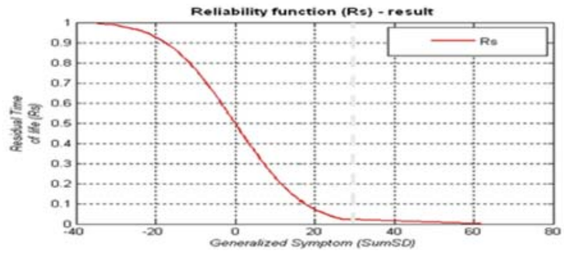

Figure 13: Reliability symptoms function of Francis turbine.

The study was made in real exploitation conditions, considering dynamic variables of generators with the purpose of obtaining information about the general technical condition of system.

REFERENCES

Bongers D. R., 2004. Development of classification scheme for fault detection in long wall systems. Brisbane, Australia.

Cempel C., 1999. Innovative Developments in Systems Condition Monitoring. Key Engineering Materials, vol 167-168, Poznan, Poland, pp. 172-188.

Cempel C., 2003. Multi - fault condition monitoring of mechanical system in operation. XVII IMEKO, Dubrovnik, Croatia. pp.1-4 .

Formenti D., Richardson M.H., 1986. Global Frequency & Damping from Frequency Response Measurements. 4th International Modal Analysis Conference, Los Angeles, CA.

International union of railways, 2003. Testing and approval of railway vehicles from the point of view of their dynamic: behaviour – safety – track fatigue – ride quality. UIC 518, Paris, France, 212p.

National Instruments, 2004. DAQ, Quick Start Guide, Austin, USA. 144p.

Natke H. G., Cempel C., 1997. Model-aided diagnosis of mechanical systems. Fundamentals, Detection, Localization, and Assessment. New York: Springer-Verlag. 248 p. ISBN 3540610650.

Natke H. G., Cempel C., 2001. Symptom observation matrix for monitoring and diagnosis. In: Journal of sound and vibration. Hanover, Germany University of Hanover. pp.609 - 613.

Potter J., Richardson R., 1984. Identification of the Modal Properties of an Elastic Structure from Measured Transfer Function Data. 20th International Symposium, Albuquerque, New Mexico.

Richardson, M., 1995. Modal Analysis Using Digital Test Systems. Seminar on Understanding Digital Control

and Analysis in Vibration Test Systems, Shock and Vibration Information Center Publication, Naval Research Laboratory, Washington D.C.
Tournay H., 2001. Guidelines to best practices for heavy haul railway operations: wheel and rail interface issues. International Heavy Haulage Association – IHHA, Missouri, USA.
Żółtowski B., Castaneda L., 2006a. Portable diagnostic system for the metro train. Diagnostyka, nr 1(37), Olsztyn, pp.39-44.
Żółtowski B., Castaneda L., 2006b. Sistema Portail de Diagnostico para el Sistema Metro de Medellin. VIII Congresso International de Mantenimiento, Bogota, Columbia.
Żółtowski B., 2007a. Diagnostic system maintenance the ability of machines. Eksploatacja i Niezawodność, Nr 4 (36) pp.72-77.
Żółtowski B, Castañeda L, Betancourt G., 2007b. Monitoreo Multidimensional de la Interfase Vía-Vehículo. Congreso Internacional de Mantenimiento, ACIEM, Bogotá, Colombia.
Żółtowski B., Castañeda L., Betancur G., 2007c. Monitoreo multidimensional de la condición (MMC) basado en la descomposición en valores singulares (SVD) Caso de estudio: sistema ferroviario. En: Revista Universidad EAFIT. Julio - Agosto - Septiembre, vol. 43, no. 147, pp. 81-94. ISSN 0120-341X.
Żółtowski M., 2011. Management information systems in fabrication engineering. ITE - PIB, Radom ISBN 978-83-7204-919-3, 271 p. (in Polish).