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JOINT MONITORING OF THE DISPLACEMENTS OF THE STRUCTURES OF A CONCRETE DAM

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ABSTRACT

The evaluation of the responses of the structures of a dam is a complex problem that requires the use of reliable and effective methods. This study makes use of factor analysis, time series and control charts for the joint analysis of monitoring data, aiming to reduce the size of the problem, help diagnose and decision making on the displacements of the structures of dam and predict the values in the medium term. The Joint Monitoring Index (IMC) resulting from the application of the method, enables global assessment of the behavior of the foothills blocks of a dam in the presence of variability in environmental conditions. The results indicate that the process is under control, it is stable and foreseeable.

Keywords: ***Monitoring of Dams, Factor Analysis, Time Series, Control Chart, IMC.***

1. INTRODUCTION

The concept of structural monitoring is associated with the development and implementation of strategies to monitor the behavior of structural systems. An efficient monitoring should aim at identifying damage at an early stage, which is usually related to local phenomena, with small magnitude [1].

The process of structural monitoring dams includes evaluating the displacements measured by pendulum, extensometer base, triorthogonal meter and multiple rod extensometer [2]–[4].

Measurements of horizontal displacements of the dam crest to its foundation are measured by associating the values observed in the direct and inverted pendulums. The extensometer base and triorthogonal meter measure the horizontal and vertical joints between relative displacements and dam blocks together. Multiple rod extensometer inform the deformability of rock masses and / or the displacement of blocks of concrete structures [4], [5].

Changes in environmental conditions such as ambient temperature in the surroundings of the dam, reservoir water level and temperature of the concrete blocks are associated with the occurrence of displacement of the concrete dam structures [2], [5], [6].

The structural safety of a dam is mainly determined by the normal operations of the structure and the social and economic benefits it provides as well as the personal and property safety of residents in the reservoir area [7]. It is therefore important to adopt reliable and effective methods to monitor the safety of the dam.

The evaluation of the responses of a dam structures, considering the instrumentation data and taking into account interaction with the environment, a problem is composed of various dimensions. Therefore, it is necessary to use techniques that allow the joint analysis of monitoring data, reduce the size of the problem and assist decision making.

In recent years the number of researchers dedicated to the study and development of models with these special purposes. Multivariate statistical models are mainly used for: system representation [8]–[10], the study of relations between the dam responses and environmental variables [7], [11], pattern recognition [12], calculating the probability of events [13], the identification of factors that influence the dam responses and forecast values [2], [6], [14]–[17], the establishment of control values [18], [19].

The aim of this study is to evaluate globally the answers of the buttresses blocks of a dam, through multivariate data analysis of displacement sensors. To this end, we created a variable called Continuous Monitoring Index, using as factors associated with the variability in the measurements of the installed instrumentation in the structures and foundations of the blocks and considering the effects of weather parameters.

2. THEORETICAL

A collection of n observations of p distinct random variables, taken from the same item, compose a multivariate sample, which can be represented in matrix form (Eq. 1), where each X_j vector containing the n observations of the variable *j*, for all $j = 1, 2, ..., p$.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots x_{1j} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots x_{2j} & \cdots & x_{2p} \\ \vdots & \vdots & \cdots\vdots & \cdots & \vdots \\ x_{i1} & x_{i2} & \cdots x_{ij} & \cdots & x_{ip} \\ \vdots & \vdots & \cdots\vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots x_{nj} & \cdots & x_{np} \end{bmatrix} \tag{1}$$

or

$$\left[\underline{X}_1 \quad \underline{X}_2 \cdots \quad \underline{X}_p\right]$$

The following are the theoretical aspects relevant to the application of factor analysis, time series modeling and construction of control charts.

2.1 Factor Analysis

Multivariate analysis provides methods and techniques for the theoretical interpretation of jointly sample. The main purposes that justify the use of multivariate analysis methods and techniques are: data reduction and structural simplification; sorting and grouping; investigation of dependence between variables; forecast; construction and hypothesis testing.

The application of multivariate factor analysis allows the explanation of the correlations between many variables of a set of data through a limited number of unobservable random variables, termed factors [20].

The factor model (Eq. 2) considers that each variable can be written as a linear combination of the common factors (F_k) and specific factors. During the process of obtaining the factors are estimated factor loadings (l_{ji}), the commonalities (h_i), the specific variances (ε_j) and factorial (f_{jk}) that are measured with explanatory properties of great interest to the researcher.

$$\left\{\begin{array}{l} Z_1 = l_{11}F_1 + l_{12}F_2 + \ldots + l_{1m}F_m + \varepsilon_1 \\ Z_2 = l_{21}F_1 + l_{22}F_2 + \ldots + l_{2m}F_m + \varepsilon_2 \\ \vdots \\ Z_j = l_{j1}F_1 + l_{j2}F_2 + \ldots + l_{jm}F_m + \varepsilon_j \\ \vdots \\ Z_p = l_{p1}F_1 + l_{p2}F_2 + \ldots + l_{pm}F_m + \varepsilon_p \end{array}\right\} \tag{2}$$

The load factor is a measure of the variable correlation with the factor. The commonality is the portion of the variance of each original variable from the extracted factors. The remainder of the variability which can be due to other factors, is measured by specific variance.

The factor scores (Eq. 3) are estimates for the values of the factors for each sample element. They may be used to sort sample components or as input variables for further statistical analysis.

$$\underline{f}_i = (L'_z L_z)^{-1} L'_z (\underline{x}_i - \underline{x}), i = 1,2,\ldots,n \tag{3}$$

2.2 Times Series

A set of observations in sequence accumulated over time, with the characteristic serial dependence is called time series [21]. Their representation (Eq. 4) is performed depending on the components: trend (T_t), seasonal (S_t), cycle (C_t) and random noise (a_t).

$$Z_t = f(T_t, S_t, C_t, a_t) \tag{4}$$

The modeling of time series is carried out by means of computational procedures leading to prediction of future values of equations, obtained directly from the past values, without the use of an underlying theory.

Models like the Auto Regressive Integrated Moving Average (ARIMA) of order (p, d, q), with p parameters in the autoregressive portion, q parameters on the moving averages and d differences are indicated for the representation of non-stationary time series [21]. For seasonal time series with serial correlation between and within the seasonal periods indicated the use of multiplicative ARIMA models $(p, d, q)\times(P, D, Q)_s$.

2.3 Control Chart

A control chart is a graphical representation made by the dataset trend graph, the axis (corresponding to the average), the upper control limit (UCL) and the lower control limit (LCL). These limits are appropriately chosen according to process variability and the adopted confidence level, so that, if the process is under control, all the sampling points will be among them.

In the event of a point to stay off limits, will evidence that the process is out of control, requiring an investigation and appropriate corrective action to find and eliminate the cause. Another process indicator out of control is the location in a systematic manner or non-random points even within the control limits. The distribution of a feature that is in statistical control is stable and predictable [22].

3. METHODOLOGY

The method proposed in this paper aims to draw up a Joint Monitoring Index (IMC) in order to assess globally the responses of the buttresses of a dam blocks, based on the displacement measured by the instrumentation and considering the impact of changes in conditions environmental. As steps of the method are described below.

The first step is the composition of the sample data matrix, with the selection of instruments, the definition of the time period, data collection, filling gaps, identifying outliers and standardization of the data, if necessary.

In the second, the sample data matrix is subjected to factor analysis in order to estimate the influence of environmental conditions in shifts, perform the ranking of the instruments according to their importance in the factor model and identify the factors that most influence the variability of the data.

The model for the IMC is prepared in the third step, through the linear combination of factors, with values estimated by the factor scores and weights determined by the weighted average of the eigenvalues of the correlation matrix.

They are then created control charts for IMC, with confidence limits of 95% and 99%. Finally, new data is entered and is held evaluation process.

The analyzes and implementations were carried out with the help of free software R (R Core Team, 2015).

4. Application in the Context of the Structural Monitoring of Dams

he proposed method was applied to a structural monitoring process of a concrete dam. The data set used consists of the observations recorded in the period between January 1990 and December 2013, which were obtained through manual measurements of the installed instrumentation in key blocks D7 and D8, the D portion (Dam Right Side, built in buttresses blocks) of the Itaipu Dam, and the hydrometeorological data from the same period.

The instrumentation comprises sensors 40 (Table 1), including direct pendulum, inverted pendulum, extensometer base and multiple rod extensometer. Hydrometeorological data were also considered: reservoir water level and temperature at the dam surroundings. Thus, 42 variables were computed, related to sensors considered in this study.

Since the frequency of measurements measured with the different instruments (sensors) was not the same, it was decided to use the monthly average of the observations. The implementation of a computational procedure allowed the generation of monthly average observations of each of the 42 sensors and identify the existence and location of gaps corresponding to periods (months) in which measurements have not been performed.

It was found that there are eight incomplete series, totaling 15 deficiencies resulting from the lack of measurements at some point. The forecast of these data was performed using ARIMA models and forecasting/backforecasting procedure.

After completing the sensor data series, we proceeded to the analysis of the Box-Plot charts and dispersion of each series, searching for the occurrence of outliers. Outliers were identified in the data reservoir water level (Figure 1). The cause of this occurrence was low rainfall in the months of the summer season of the years 1999/2000 and 2012/2013. It was decided to keep the values as observed, to check the influence of this occurrence in the dam answers.

The application of factor analysis principal component resulted in a model composed of five factors identified based on the greatest factor loadings of sensors, able to explain 91.12% of the variance of the set of observations. Thus, it obtained a reduction in the size of the problem, with minimal loss of information because the factors have come to represent the set of original variables.

The factors were named according to the sensors more correlated with them, that is, as the greatest factor loadings. The first factor, due to its positive correlation with most multiple gages sensors rods, corresponds to the "Founding of Changes" (MF). This was the most important factors identified, it accounts for 45.88% of the observed variability in the data set.

The second factor, called "Horizontal Moving the Structure in the Normal Direction" (MHESN) explained 30.83% of the variance and is associated with the openings of the joints between the dam blocks and horizontal displacement in the normal direction (perpendicular to the direction of flow water).

The "Horizontal Moving the Structure in the Flow Direction" (MHESF) third factor identified, accounted for 9.66% of the variability. The dominant factor in the variables was the temperatures of the sensors and shifts in the horizontal direction of the water flow from block D8.

The fourth and fifth factors, called "Geometry of Structure of D7 Block" (GEBD7) and "Hydrostatic Pressure" (PHI), were related to horizontal displacements in the direction of D7 block water flow and the reservoir water level, respectively. Furthermore, the GEBD7 factor accounted for 2.41% of the total variability, while the influence of PHI was 2.34%.

The variability in the readings of each sensor, arising identified factors were estimated by commonality. Using this as a measure of the importance of each variable to the factorial model, there was obtained the ranking of the sensors. So the most important instruments for the D7 and D8 blocks were respectively multiple rod extensometer Z33, Z34, Z35 (even borehole) and extensometer base (opening) Z7, Z9. Furthermore, the reservoir water level (Z42) was related to the variable environmental conditions highest ranking.

The factor, being a latent variable, cannot be measured directly. Thus, the values of factors, called factor scores were estimated on the basis of factor loadings and the sensor values that dominate this factor. Figure 2 shows the time series of the five factors.

Considering that MF, MHESN, MHESF, GEBD7 and PHI are quantitative variables that are related to the variability of the dam answers, these factors were used as parameters for the preparation of the Joint Monitoring Index (IMC). The formulation of this index (Eq. 4) consisted of the linear combination of factors, whose weights were obtained from the weighted average of the eigenvalues of the correlation matrix sample.

$$\text{IMC} = 0.46\text{MF} + 0.31\text{MHESN} + 0{,}10\text{MHESF} + 0.02\,\text{GEBD7} + 0.02\,\text{PHI} \qquad (4)$$

This index concentrates the information of the factors which, in turn, represent the sensors of the set of observations used in this study. Therefore, IMC has great potential for information about the behavior of blocks D7 and D8 dam and can be used in monitoring.

To make it easier monitoring this new variable was drawn up the control chart (Fig. 3) for IMC, with limits set to two three standard deviations, i.e., 95% and 99% probability values fall between these limits, respectively. Noting the letter of control, it was found that the process was under control (stable), which allowed the prediction of the values for the next 24 months.

To check the quality of the model fit, we collected new data for the months of January 2014 to August 2015, calculate the new values of the factor scores and IMC. Then the results obtained were plotted in the control chart (Fig. 4).

The IMC values for the new data remained within established limits and within the range of the forecast confidence interval shown in Figure 3. Therefore, the model was considered adequate to represent the responses of blocks D7 and D8 dam subject to the effect of temperature variations and the reservoir water level. Therefore, IMC can be used to assess the overall behavior of blocks.

CONCLUSION

The method proposed in this paper consists in the multivariate analysis of the displacements of the structures and foundations of a concrete dam, taking into account the interaction with the environment.

Most of the measurement data variability is due to factors: Foundation's Movement; Horizontal Movement Structure in Normal Direction; Horizontal Movement Structure in the Flow Direction; Block D7 Structure Geometry and Hydrostatic Pressure.

The Monitoring Index Joint, designed based on the identified factors, was suitable for the representation of the structural behavior in a unified manner and can be used as additional information in dam monitoring.

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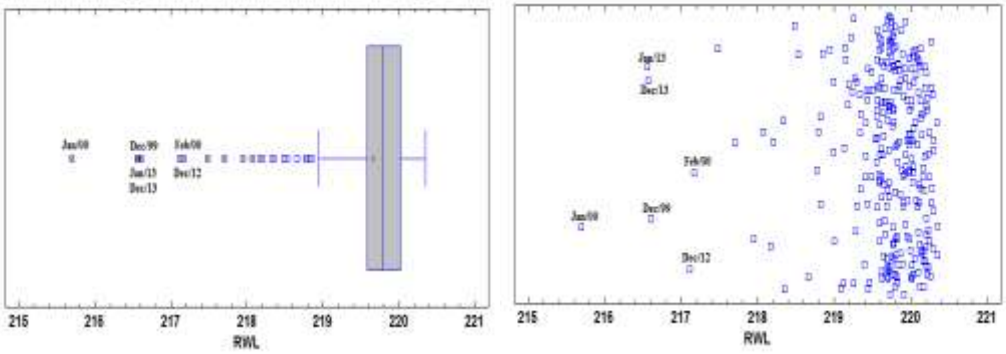
Table 1: Phenomena monitored by instruments and respective sensors

Phenomena	**Instrument**	**Sensors**
Radial displacement	Direct pendulum	Z1, Z5
Radial displacement	Inverted pendulum	Z3
Tangential displacement	Direct pendulum	Z2, Z6
Tangential displacement	Inverted pendulum	Z4
Opening and closing of joints between blocks	Extensometer base	Z7, Z9, Z11, Z13, Z15, Z17
Horizontal sliding between blocks	Extensometer base	Z8, Z12, Z14, Z18
Differential settlement between blocks	Extensometer base	Z10, Z16
Surface temperature of block	Concrete thermometer – downstream	Z19
Surface temperature of block and water reservoir	Concrete thermometer – upstream	Z20
Deformations of rocky massive	Multiple rod extensometer	Z21, ..., Z40
Ambient temperature	Thermometer	Z41
Reservoir water level	Limnimetric Ruler	Z42

Figure 1: (a) Box-Plot and (b) Scatterplot graphic of the reservoir water level (RWL) from Itaipu dam, from Jan /90 to Dec /13



(a) (b)

Figure 2: Time series of main factors that influence the movements of the concrete structures of the Itaipu dam, from Jan/90 to Dec/13

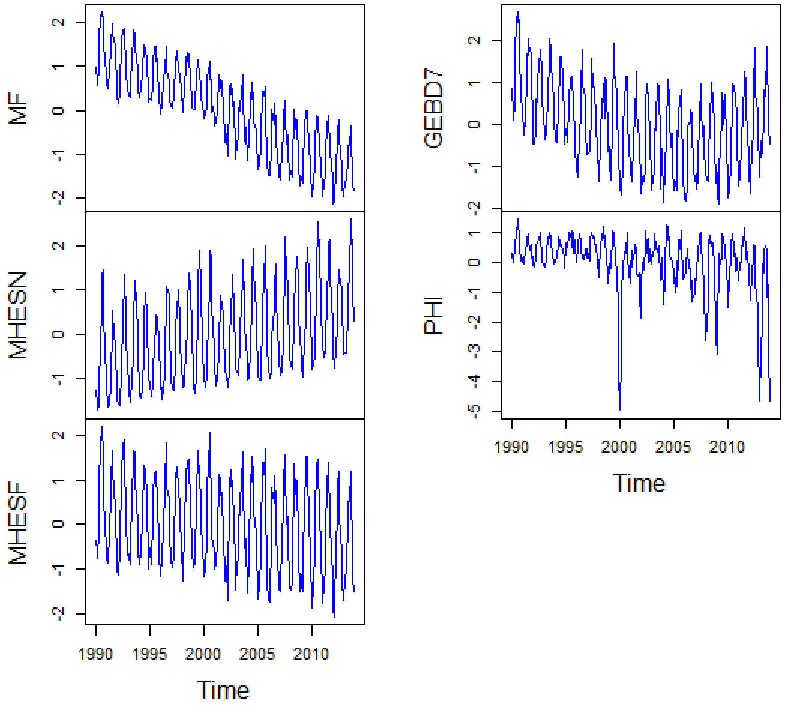


Figure 3: Control chart for the Joint Monitoring Index (IMC)

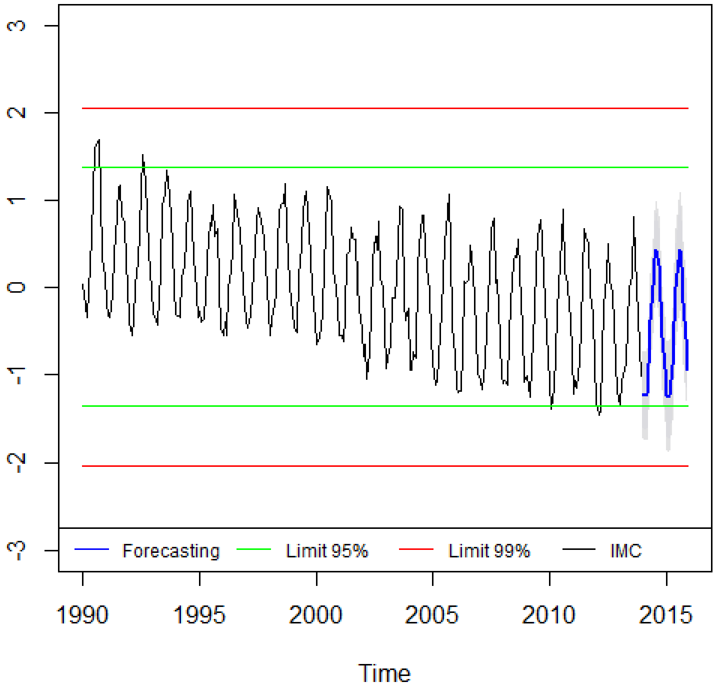


Figure 4: Control chart from the updated IMC