Jan. 2016. Vol. 8. No. 01 ISSN2305-8269
International Journal of Engineering and Applied Sciences

www.eaas-journal.org

DETERMINATION OF MATHEMATICAL MODEL FOR APPLICATION OF THE RELIABILITY OF STRUCTURAL ANALYSIS IN MONITORING AND CALCULATION OF RISK PROBABILITY IN CONCRETE BLOCKS OF ITAIPU DAM

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ABSTRACT

Structural Reliability analysis is a mathematical technique applied to engineering that aims to study the behavior of geotechnical structures. This study aims to determine a mathematical model capable of monitoring a highly instrumented concrete structure, and through it perform the calculation of failure probability of a structural complex system. The proposed model is formulated from the method that uses the techniques of multivariate analysis to determine the possible failure modes to be monitored and their critical regions. Using this method we propose to define a performance multivariable function, where variables are involved only the readings obtained by means of the instruments installed in the concrete block. This prevents the use of physical quantities commonly employed and consequently a simpler performance function without the multiple integral calculation and employing linear programming techniques necessary to carry out the calculation of the probability of failure.

Keywords: ***Factor Analysis. Failure Modes. Performance function, Failure Probability.***

1. INTRODUCTION

Dams are built to impound, store or divert water to get some benefits with its use. Unfortunately, the damming of water, sometimes poses a potential risk of public safety. The purpose of a dam safety program is to recognize the potential dangers and reduce them to acceptable levels. Safe dams can be built, and dams with safety deficiencies or potential deficiencies can usually be corrected with the correct application of current technologies when those resources are available.

Gravity dams should be built with concrete meeting the design criteria for strength, durability, permeability and other required properties. Concrete Properties vary with age, type of cement, aggregates, and other ingredients, and their proportions in the mixture. As different concrete gain strength at different rates, laboratory tests should be performed at old enough ages to allow evaluation of the final strengths [1].

The elastic properties of concrete are useful to analyze deformations related to differential movements of the block, three-dimensional analysis and other aspects that may cause deformations. The modulus of elasticity, although not directly proportional to the concrete strength increases with the concrete strength increase. As it happens with the strength properties, the tensile modulus is influenced by mixing proportions of cement, aggregates, additions and age. For a concrete dam, the insertion of instruments to monitor some of the important parameters related to the performance is justified. These parameters can include uplift on the foundations, water levels to downstream, and the internal or superficial movement. Instruments located on strategical positions and monitored according to a defined chronogram can provide inestimable information about what could be unfavorable performance tendencies [1]. More information about instrumentation, dams project the gravity and

ISSN2305-8269
International Journal of Engineering and Applied Sciences

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concrete dams' instrumentation can be found at [3], [4] e [5].

On this article we propose in order the determination of a multivariate performance function, which is be able to carry out the monitoring of a concrete block of a highly instrumented dam. For this purpose, it is used a method shown by [6], which enables the determination of possible failure modes to be monitored, and, in addition, provides the critical regions of each failure event.

This methodology was applied in key block A-15 of the Itaipu dam and enabled the determination of five anomalies and their critical regions. The results obtained with this application are available in [7], and on this work a brief summary of these results is presented.

We intend to use this information to develop a mathematical model, using only the data of the readings of the instruments installed on concrete block in study. This model, when implemented in any software, can access the Itaipu database and will be able to identify when a fault is occurring or imminent to occur, serving as another tool in decision-making, enabling an early action of dam professionals.

By using only the instrumentation data, this model does not require physical measures commonly employed, such as friction coefficient, hydrostatic pressure, pack weight, etc. making it possible to define a simpler performance function. Moreover, with the aid of structural reliability techniques, we can determine the failure probability of each event and the complete structural system without being necessary the integral multiple calculation and the use of Linear and Nonlinear Programming techniques.

2 STRUCTURAL RELIABILITY:

The Structural Reliability Analysis deals with the relationship between charges imposed on a system and its ability to bear them. Both load and resistance may be uncertain, so that the result of the interaction is also uncertain. Today, it is common to express the condition of a structure as a reliability index, which can be related to the probability of failure [8]. It should be understood in this context that "failure" includes not only catastrophic failure, as in the case of a landslide, but also, as an unacceptable difference between the observed and expected performance [9].

Based on conventional formulation structural reliability, to obtain the failure probability of a structure, it is essential to define the vector of random variables X given by:

$$\underline{X} = (X_1, X_2, \dots, X_n)^t \tag{1}$$

that corresponds to the uncertainty associated with the design, such as the request imposed on the structure, strength, geometry and materials. The function performance, illustrated in Equation (2),

$$H(\underline{X}) = H(X_1, X_2, \dots, X_n) \tag{2}$$

establishes a boundary between the fault domain and the secure domain, ie,

$$D_f = \{\underline{X}; H(\underline{X}) < 0\} \tag{3}$$

is the fault domain,

$$D_s = \{\underline{X}; H(\underline{X}) > 0\} \tag{4}$$

is the security domain.

The limit state equation is defined by $H(\underline{X}) = 0$. Consequently, the probability of failure can be evaluated by:

$$P_f = \int \cdots \int_{H(\underline{X})<0} f_X(X_1, \cdots, X_n)\, dx_1 \cdots dx_n \tag{5}$$

at where $f_X(X_1, X_2, \cdots, X_n)$ is the joint probability density function for the vector of random variables and integration is performed on the fault field, $H(\underline{X}) \leq 0$.

For [12] the calculation of failure probability by assessing the multiple integral is not easy, due to the following reasons:

1 it involves a multi-dimensional integral;

2 The exact shape of the density function of joint probability of the random variables is rarely known;

3 The limit state equation $H(\underline{X}) = 0$. is not always given in an analytical way, but as the solution of some numerical algorithm.

For this paper´s purpose, it is defined a multivariate performance function, where the random variables involved are only obtained through the readings of the instruments, and the calculation of failure probability does not require the evaluation of a multiple integral, nor the use of linear programming techniques. For this, we use the methodology to determine the failure modes presented in the following sections.

ISSN2305-8269
International Journal of Engineering and Applied Sciences

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3. THE DETERMINATION OF FAILURE MODES:

The determination of the failure modes of a highly instrumented concrete structure was a paper presented by [6]. Applying a multivariate analysis technique known as factor analysis, it determined groups of instruments that are highly correlated. These groups are known as factors and through them it is possible to generate the factor scores, which are random variables that replaced the initial random variables (readings of instruments) simplifying the analysis. With the knowledge gained after the factor analysis and correlation of the instruments with possible anomalies, it was developed a method to determine the critical regions of each failure mode.

This method consists of carrying out simulations in the readings of the instruments in a way that each abnormality was induced, and for each anomaly, a large number of simulations were performed, generating various vectors with synthetic data that simulate the same fault. With these vectors, it is done the calculation to generate the factor scores, a technique presented in several Multivariate Analysis of books such as [10] e [11].

In that context, it was regarded as "failed structure" a sudden change in the behavior, not necessarily a catastrophic action, but a warning that something abnormal is happening, and if it is not repaired, this anomaly may occur. [6] used only the factor scores that had a distribution and probability normal to the method application.

The requirement of normality condition reduced the method's efficiency, because they eliminated the analysis of some factors, where possibly an important set of instruments was linked by restricting the number of possible anomalies to be monitored.

For the proposed article, changes in the data are applied with the objective of transforming random variables with probability distribution into any random variables with normal probability distribution. Therefore, it is used changes suggested in [12] and that preserves behavior change.

Considering only the factor scores that already have a normal probability distribution and those where it was possible to find a function that turns the data into normal, necessary condition to determine the critical regions, it is possible after identifying the instruments that are associated with factors, to generate vectors that simulates an anomaly.

A description of the method for determination of possible failure modes to be monitored, and the application of this technique in an Itaipu concrete block is presented in [7]. In this article, we present the algorithm that generates the vectors that simulate each failure mode, represented by the flowchart in Figure 2. The next section aims to summarize the results obtained from the application of the method of determination of the failure modes conducted in key block A-15 of the Itaipu Dam.

4. APLICATION OF THE METHOD TO A KEY BLOCK OF ITAIPU

It was applied the methodology to determine the failure modes in the concrete block from the Itaipu dam. The materials used were the random variables generated by the readings of the instruments installed in the key block A-15, spillway block. In total, 50 instruments were analyzed, the vast majority installed only in block A-15, but some instruments also belong to the D-1 and A-14 blocks because they are installed at the boundary of these blocks to monitor the openings, settlements and landslides. Figure 1 shows the selected Itaipu block.

The instruments installed in Itaipu dam and the functions they perform in the structure are found in [13]. The functional description of the instruments installed in the A-15 block are available in manual System Operation and Maintenance of Itaipu (SOM) and were presented in [14].

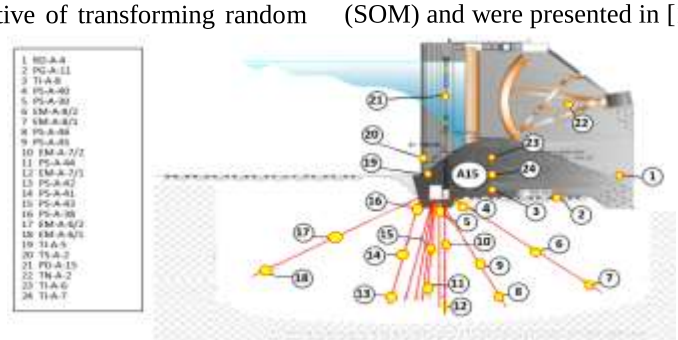

Figura 1: Block A-15 of Itaipu Dam

 ISSN2305-8269
International Journal of Engineering and Applied Sciences

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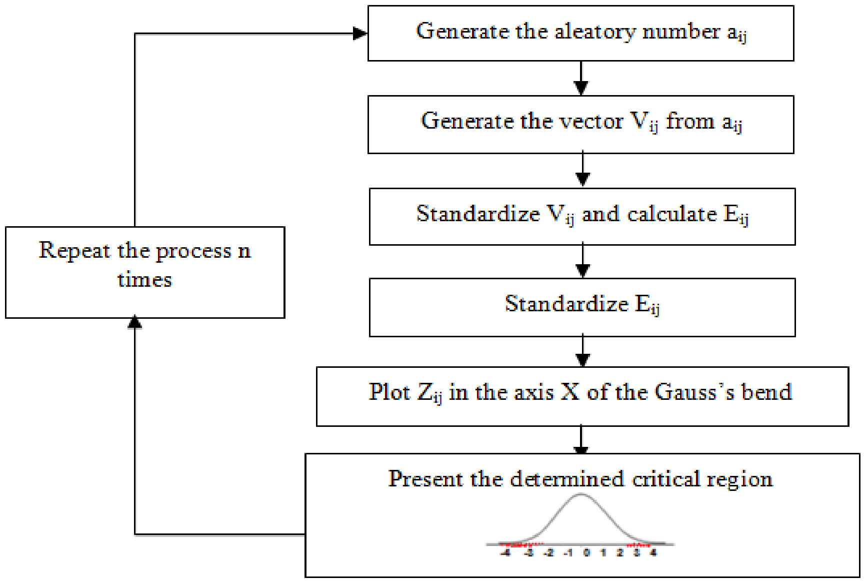

Figura 2: Algorithm flowchart to derermine the failure modes

A matrix was created $M_{168\times50}$ Multivariate with the readings generated by the instruments shown in Chart 1 together with other two instruments that measure the temperature and level of the reservoir. The time period considered was from January 2000 to December 2013. In order to enable the analysis of the data, the readings were standardized monthly.

Before application of the factor analysis in the matrix $M_{168\times50}$ using Statistica Software, it was observed some statistical indispensable tests for the method. Statistical tests are presented in [7] and the results obtained by the tests are shown in Chart 1.

Chart 1: Statistical Tests

Test	Statistics	Test Decision
Multivariate Normality (distance of Mahalanobis)	p = 0,7626	Multivariate Normality cannot be excluded.
Bartlett Sphericity Test	$\chi^2 = 7988{,}4, \quad p = 0$	The correlation matrix is different from the identity matrix.
Data Suitability Measurement	$KMO = 0{,}8348$	The data are adequate to the factorial analysis application.

Test results proved, it was applied the factor analysis in matrix $M_{168\times50}$. The method adopted to obtain the factorial coefficients was the main method of components with Varimax rotation, as this method achieved a larger portion of the explained variance, compared to the method of maximum likelihood.

To determinate the factor scores, a Kaiser test was applied, and after eliminating two variables with low commonalities, it was held again the factor analysis involving all statistical tests performed before, but now in matrix $M_{168\times50}$ to reconfirm adequacy of the data. Again all tests were successful and the new analysis obtained an explained variance of 87.30%, with no variable with low commonality.

The factor scores generated from the factorial coefficients were used to determine the failure modes. Them was applied the univariate normality test known as Lilliefors test to verify the normality of the data. In cases where normalcy was not proved, it was necessary to apply changes in scores. The variables that passed the tests were standardized and used in the simulations of the anomalies.

Chart 2 shows the results obtained after the statistical tests applied and transformations.

ISSN2305-8269
International Journal of Engineering and Applied Sciences

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Chart 2: Lilliefors Test

Scores	Estimations	Transformation	Estimations	Test Decision
1	d=0.1209, p<0.05	$\sqrt{\lvert x_i \rvert}$	d=0.0520, p>0.20	Normal
2	d=0.1470, p<0.01	no		
3	d=0.0713, p<0.05	no		
4	d=0.0553, p>0.20	-		Normal
5	d=0.0037, p>0.20	-		Normal
6	d=0.0847, p<0.01	no		
7	d=0.0336, p>0.20	-		Normal
8	d=0.1246, p<0.01	no		
9	d=0.1491, p<0.01	$\sqrt{\lvert x_i \rvert}$	d=0.4487, p>0.20	Normal

According to the factor analysis it was generated groups of instruments that are highly correlated. Chart 3 shows these groups.

Chart 3: Group of instruments highly correlated

GENERATED GROUPS				
FACTOR 1	FACTOR 4	FACTOR 5	FACTOR 7	FACTOR 9
Pendulum	R. D 5/tr 1	RD 6/tr4	RD 4/tr1	Piezometer 41
Termometer	R. D 5/tr 2	RD 6/tr5	RD 4/tr2	Piezometer 43
Stress Meter	R. D 5/tr 3	RD 6/tr1	RD 4/tr3	Piezometer 45
JS-A and JS-D	R. D 5/tr 4		RD 4/tr4	
Environment Temp.	R. D 5/tr 5			
Piezometer 46				

Based on what is presented in the literature such as [2], [15] e [16] and the practical knowledge of professionals in security Itaipu dam was possible with these groups to monitor the following anomalies: Sliding, Creep, Uplift, and Overturning.

To determine the critical regions of these anomalies it was used the algorithm represented by the flowchart shown in Figure 1. To determine each failure region 2500 simulations were conducted, where only the instruments related to a particular anomaly had values within the behavior change intervals using for it only the factors which have influence to that anomaly, determining the corresponding critical region. The critical regions for the key block Itaipu were presented in [7] graphically, this article these regions are shown in Table 4. Each region guarantees a percentage of 90% accuracy, because it was considered only the range of straight where there was a large concentration of these simulation points.

Chart 4: Factors Association with the anomalies and critical regions

Index	Anomaly	Factors	Critical Regions
1	Sliding Breccia D	1 e 9	(1.65;2.1) ∩ (0.42; 0.95)
2	Uplift breccia D	1	(2.4; 3.1)
3	Sliding Joint D	1	(2.1;2.6)

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4	Creep	4, 5 e 7	[(-2.3;-1.6)U(1.6;2.3)]∩[(-1.16;-0.83)U(0.83;1.16)]∩ [(-1.25; -0.9)U(0.9;1.25)]
5	Overturning	1, 4, 5, 7 e 9	(-2.9;-1.4) ∩[(-0.81;-0.57)U(0.58;0.81)] ∩ [(-1.165;-0.82)U(0.83;1.155)] ∩ (-1.258;-0.89)U(0.897;1.249)]∩ (0.42;0.95)

5. MATHEMATICAL MODEL FOR GENERAL CASE

At this time, we are able to define the mathematical model that will seek to carry out the monitoring of a key block of a highly instrumented concrete dam, where the instruments are correlated. For the general case, we assume the assumptions required in[6]:

1. The sample data matrix is derived from a multivariate normal population;

2. All the necessary statistical tests were successful;

3. The Factor Analysis was successful, providing an explanation of the higher variability to 75%;

4. All Factorial scores have a normal distribution.

Now suppose that there are n instruments installed on the block, and after factor analysis it was obtained j factors. Suppose also that the instruments installed in the block are able to monitor anomalies i, and for each anomaly exists a number $m \leq n$ instruments able to identify i.

If a single factor m have the instruments with high contribution to this factor, able to monitor the anomaly I, then only this factor will be enough to diagnose this anomaly. If any m ≤ n instruments able to identify the fault I, with this instrument spread in some factors with high contribution, so all these factors are needed to monitor i.

Therefore, considering a block of a concrete dam, where it was determined anomalies, which the instruments are able to monitor and, where critical regions of the anomalies have been identified through the algorithm shown in Figure 1, you can define a function performance capable of performing the monitoring, however, before it must be defined:

1º G_i is the component of performance function that monitors the anomaly i;

2º K_{ij} is a group formed only by j factorial scores that relate the anomaly i;

3º k_i is the number of factors related least one, or,

$$k_i = \# \{K_{ij}\} - 1 \quad (6)$$

So given $\underline{Z} = (z_1, z_{2,} \dots, z_j)$ the vector of the factor scores transformed into normal random variables default, the performance function is defined as $G(\underline{Z})$, given by:

$$G(\underline{Z}) = \begin{cases} G_1(\underline{Z}) = \lambda_{11}z_1 + \lambda_{12}z_2 + \cdots + \lambda_{1j}z_j + k_1 \\ G_2(\underline{Z}) = \lambda_{21}z_1 + \lambda_{22}z_2 + \cdots + \lambda_{2j}z_j + k_2 \\ \vdots \\ G_i(\underline{Z}) = \lambda_{i1}z_1 + \lambda_{i2}z_2 + \cdots + \lambda_{ij}z_j + k_i \end{cases}$$

with:

$$\begin{cases} \lambda_{ij} = 0 \quad j \notin K_{ij} \;\; ou \;\; z_j \notin RC_{ij} \\ \qquad\qquad se \\ \lambda_{ij} = \dfrac{-1}{z_j} \qquad z_j \in RC_{ij} \end{cases} \quad (7)$$

λ_{ij} where is the coefficient of the anomaly of the i factor j score z_j represents the value of the factor score standardized j and RC_{ij} represents the critical regions defined by the anomaly was from the factorial score j.

Note that the value given by constant λ_{ij} depends on whether the z_j value belongs to their respective critical region and the j factor has influence with the i anomaly. So, with this function we come to the following conclusions:

1º $G_i(Z) \geq 0$ $\forall i$ only when no abnormality has occurred;

2º $G_i(Z) < 0$ some i when one or more anomalies occurred;

3º index i indicates anomalies which can be monitored by the performance function and j index indicate which factors are responsible for the occurrence of the abnormality, and consequently instruments which showed values outside their normal range.

We obtain, thanks to the factor analysis, a multivariate performance function, where each component is a function of a linear combination of independent standard normal random variables with each other, and therefore possess this probability distribution. Although this function does not use the physical variables typically employed in reliability analysis to determine the performance function, it preserves the condition to assume values smaller than zero only when one or more anomalies occurs.

6. FAILURE PROBABILITY

It is intended to calculate the probability of failure from the performance function (7). The idea is to use the basic concepts of probability and ownership of the factor scores generated are independent normal random variables with each other (which is a result of factor analysis) in each component of the performance function. Thus, it can be said that a failure has occurred in the structure when there is I such that $G_i(Z) < 0$. Soon

$$P\left[G(\underline{Z}) < 0\right] = P\left[\bigcup_{n=1}^{i} G_i < 0\right] \quad (8)$$

Note that the calculation of the probability of failure of each G_i event may be performed using the simple probability techniques G_i since all components are linear combinations of standard normal random variables that are independent of each other.

Thus we can find the probability of failure of each individual event, and assuming independent G_i, events can find an estimate of the probability of structural failure of the entire system. Note that for any *j* the function has the form components 1.6

$$G_i = \lambda_{i1}z_1 + \lambda_{i2}z_2 + \cdots + \lambda_{ij}z_j + k_i \quad (9)$$

Thus,

$$\begin{aligned} P[G_i < 0] &= \\ P\left[\lambda_{i1}z_1 + \lambda_{i2}z_2 + \cdots + \lambda_{ij}z_j + k_i < 0\right] &= \\ P\left[\lambda_{i1}z_1 + \lambda_{i2}z_2 + \cdots + \lambda_{ij}z_j < -k_i\right] &= \\ P\left[(z_1 \in RC_{i1}) \cap \ldots \cap (z_j \in RC_{ij})\right] &= \end{aligned} \quad (10)$$

As z_i are all random variables independent from each other we have to

$$P[G_i < 0] = P[z_1 \in RC_{i1}].P[z_2 \in RC_{i2}] \cdots P\left[z_j \in RC_{ij}\right] \quad (11)$$

So, to $RC_{nj} = (Inf_{nj}, Sup_{nj})$ with $n = 1, \ldots, i$ we have to

$$P\left[z_i \in RC_{ij}\right] = \int_{inf_{ij}}^{sup_{ij}} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz \quad (12)$$

And, therefore, the probability of failure of the event G_i is given by:

$$P[G_i < 0] = \int_{inf_{i1}}^{sup_{i1}} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz \cdots \int_{inf_{ij}}^{sup_{ij}} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz \quad (13)$$

Proceeding this way for all events G_i, and assuming independent events, it is found an estimate for the probability of failure of the concrete blocks given by:

$$P\left[G(\underline{Z}) < 0\right] = P\left[\bigcup_{n=1}^{i} G_i < 0\right] = P[G_i < 0] + P[G_2 < 0] + \cdots + P[G_i < 0] \quad (14)$$

7. MATHEMATICAL MODEL FOR THE APPLIED CASE

To set the performance function for the applied model it is used the information shown in Chart 4. In this Chart, it is observed that for the A-15 Itaipu block, it was possible to monitor five anomalies and which factors are responsible for monitoring them; Chart 4 also presents the respective critical regions of each anomaly. Therefore, for this case the performance function has the following form:

$$G(\underline{Z}) = \begin{cases} G_1(\underline{Z}) = \lambda_{11}z_1 + \lambda_{19}z_9 + 1 \\ G_2(\underline{Z}) = \lambda_{21}z_1 \\ G_3(\underline{Z}) = \lambda_{31}z_1 \\ G_4(\underline{Z}) = \lambda_{34}z_4 + \lambda_{35}z_5 + \lambda_{37}z_7 + 2 \\ G_5(\underline{Z}) = \lambda_{41}z_1 + \lambda_{44}z_4 + \lambda_{45}z_5 + \lambda_{47}z_7 + \lambda_{49}z_9 + 4 \end{cases} \quad \text{with} \quad \begin{cases} \lambda_{ij} = 0 & z_j \notin RC_{ij} \\ & se \\ \lambda_{ij} = \dfrac{-1}{z_j} & z_j \in RC_{ij} \end{cases} \quad (15)$$

The performance function given by Equation (15) defined above is capable of diagnosing when one of the anomalies described in Chart 5 may be occurring, or on the verge of occurring, it is only necessary that one of the components of this function assumes a value smaller than zero.

From the performance, function shown in Equation (15) can perform calculation of an estimated probability of failure of each fault shown in Chart 5. To obtain these results was used Matlab software, which has implemented the probability calculation normal random variables.

 ISSN2305-8269
International Journal of Engineering and Applied Sciences

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Sliding Breccia D

$$P[G_1 < 0] = P[\lambda_{11}z_1 + \lambda_{19}z_9 + 1 < 0] = P[\lambda_{11}z_1 + \lambda_{19}z_9 < -1] = P[(z_1 \in RC_{11}) \cap (z_2 \in RC_{19})] = \int_{1,65}^{2,1} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz . \int_{0,42}^{0,95} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz = 0.005253 \quad (16)$$

Sliding Joint D

$$P[G_3 < 0] = P[\lambda_{31}z_1 < 0] = P[(z_1 \in RC_{31})] = \int_{2,1}^{2,6} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz = 0.013203 \quad (18)$$

Uplift breccia D

$$P[G_2 < 0] = P[\lambda_{21}z_1 < 0] = P[(z_1 \in RC_{21})] = \int_{2,4}^{3,1} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz = 0.007230 \quad (17)$$

....

Creep

$$\begin{aligned} P[G_4 < 0] &= P[\lambda_{44}z_4 + \lambda_{45}z_5 + \lambda_{47}z_7 + 2 < 0] = P[\lambda_{44}z_4 + \lambda_{45}z_5 + \lambda_{47}z_7 < -2] \\ &= P[(z_4 \in RC_{44}) \cap (z_5 \in RC_{45}) \cap (z_7 \in RC_{47})] \\ &= \left[\int_{-2,3}^{-1,6} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz + \int_{1,6}^{2,3} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz\right] . \left[\int_{-1,16}^{-0,83} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz + \int_{0,83}^{1,16} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz\right] . \\ &\quad \left[\int_{-1,25}^{-0,9} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz + \int_{0,9}^{1,25} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz\right] = 0.002219 \end{aligned} \quad (19)$$

Overturning

$$\begin{aligned} &P[G_5 < 0] = P[\lambda_{51}z_1 + \lambda_{54}z_4 + \lambda_{55}z_5 + \lambda_{57}z_7 + \lambda_{59}z_9 + 4 < 0] = \\ &P[\lambda_{51}z_1 + \lambda_{54}z_4 + \lambda_{55}z_5 + \lambda_{57}z_7 + \lambda_{59}z_9 < -4] = \\ &P[(z_1 \in RC_{51}) \cap (z_4 \in RC_{54}) \cap (z_5 \in RC_{55}) \cap (z_7 \in RC_{57}) \cap (z_9 \in RC_{59})] = \\ &\left[\int_{-1,258}^{-0,89} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz + \int_{0,897}^{1,249} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz\right] . \left[\int_{0,42}^{0,95} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}z^2} dz\right] = 0.000051 \end{aligned} \quad (20)$$

8. RESULTS AND DISCUSSION

Through the method of determining the possible failure modes to be monitored, it was developed a mathematical model to monitor a highly instrumented concrete block. This model assumes, in its components, values smaller than zero only when a fault is detected; therefore, it is called multivariate performance of function, which is represented by the function (7).

The performance function proposed in this paper uses only as variables the values of the factor scores, which have normal probability distribution, obtained from a matrix generated readings of instruments installed on the concrete block under consideration. And for not presenting higher numbers than one and a product of the variables involved, it is a multivariable function where each component is a linear function. For this simplicity, the function (7) has the following advantages over other conventional methods of structural reliability:

1º Low computational cost, does not involve complicated operations to determine the values of each component;

2º Not using parameters as variables related to the concrete characteristics such as coefficient of friction, elasticity and strength, which often require testing on samples taken from block;

3º The calculation of the probability of failure from the performance function (7) is relatively simple, it involves only normal random variables that are independent of each other, thanks to a property of factor analysis.

Applying the method at the block A-15 of the Itaipu dam, it was obtained the performance function (15). This function has only five components because, in carrying out the factor analysis we obtained only five factor scores with normal probability distribution, and of these, two scores required a transformation. For this case, the performance function obtained is able to monitor landslides, uplift, fluency/creep and tipping.

From the function (15), using the information presented in Chart 5, it was calculated the failure probability failure of each one of these anomalies. The results in Chart 6 are simplified.

Chart 5 – Failure Probability

$G(\underline{Z})$	Anomaly	$P[G_i < 0]$
G_1	Sliding Breccia D	0.005253
G_2	Uplift breccia D	0.007230
G_3	Sliding Joint D	0.013203
G_4	Creep	0.002219
G_5	Overturning	0.000051

In Table 6 we estimate the probability of failure of each fault monitored at block A-15 from the Itaipu dam. The results show a low probability of occurrence of these anomalies, showing that the block under consideration is stabilized and shows no eminent risk.

9. CONCLUSION

The scientific contribution presented in this work was the use of the methodology that determines the possible failure modes to be monitored in defining a multivariate performance function capable of monitoring a structural complex system in a simpler way than conventional methods of structural reliability applied the geotechnical systems.

The performance function, applied to the case, provided estimates of failure probabilities of each possible anomaly to be monitored at the block A-15 from the Itaipu dam. These results serve to provide an indication of the block condition, however, as a failure to our case is a change in the behavior, each time it is performed the calculation of the factor scores from monthly readings of instruments, we can obtain values of the performance function components (15). So, if any component has values smaller than zero, it should be understood as a prediction that something is not in accordance with the normal behavior of the structure, serving as a prediction of these anomalies, if this result is maintained for a certain period.

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ISSN2305-8269
International Journal of Engineering and Applied Sciences

www.eaas-journal.org

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