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Application of a Methodology for Updating Numerical Predictions of a Tailings Dam

Aplicación de una Metodología de Actualización de Predicciones Numéricas en una Presa de Relaves

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ABSTRACT: The mining industry plays a crucial role in the global economic development, highlighting the importance of a continuous evaluation in the physical stability of tailings deposits. All the analysis methods have limitations, and the geotechnical field monitoring is essential to understand the behavior of the geomaterials as the projects progress. There is a need to make use of the in-situ measurements, improving the numerical predictions associated with the physical stability of the deposits. In this context, the methodology proposed by Corral (2013) is presented as an effective solution for the soil parameter update. Using sensitivity analysis, the maximum likelihood approach, and the genetic algorithm as an optimization method to solve the inverse problem. This methodology is applied by integrating MATLAB and PLAXIS through Python. Its implementation allows reducing the uncertainty in the numerical model and obtaining more accurate predictions. Likewise, it is possible to predict with greater certainty and safety the future behavior of the following construction stages of the deposit, providing extremely valuable information for decision making in the projects.

KEYWORDS: Tailings dam, numerical analysis, parameter update, prediction improvement

1 INTRODUCTION

The economic development of many countries is linked to the mining industry, generating a continuous increase in the production of tailings. This entails a significant increase of the potential risks in the tailings dam, due to the need to build larger deposits to accommodate the growing production of tailings (Morrison, 2022).

In recent years, catastrophic collapse events have been recorded worldwide, highlighting the urgency of continuously evaluating the physical stability ensuring its long-term sustainability. In practice, the limit equilibrium analysis is routinely used, but unfortunately, this method cannot provide any information about the deformations. This great limitation is aggravated even more when the problem requires coupled analyses to properly diagnose the physical stability. The finite element and finite difference methods allow solving this great limitation; however, other limitations persist related to deterministic models, where there are generally discrepancies with the in-situ measurements.

In recent years, parameter update methods have been developed in the field of geotechnics, using the inverse analysis at the element scale and instrumentation in geotechnical works.

In the inverse analysis at the element scale, results of great interest have been obtained, since the parameters found through the genetic algorithm present favorable adjustments (Rokonuzzaman & Sakai, 2010; Samarajiva et al., 2005). Also, the calibration of parameters has been carried out using robust and interpolation-free technique (RIFT) through the particle swarm optimization method, obtaining excellent results (Lin et al., 2015).

In the case of excavations, inverse analysis has also been carried out with various optimization techniques, such as Bayesian updating, particle swarm, error domain falsification approaches (EDMF), genetic algorithm, among others (Baroth & Malecot, 2010; Levasseur et al., 2008; Lin et al., 2015; Rechea et al., 2008; Ze-Zhou et al., 2018). However, they have all shown a clear tendency towards the use of a single type of instrumentation to measure the deformations in retaining walls, and many times the measurements used for the parameter update are synthetically generated. In the case of embankments and tailings deposits, inverse analyses have also been shown with interesting results through Bayesian updating and genetic algorithm, using more than one instrument (Grosel, 2021; Zheng et al., 2018).

This demonstrates that geotechnical field monitoring plays a significant role, as it allows understanding the real behavior of the geomaterials as the project progresses. Therefore, there is a need to make use of the in-situ measurements through inverse analyses, improving the numerical predictions associated with the physical stability of these deposits. The methodology for updating numerical predictions proposed by Corral (2013) has proven to be highly efficient in the parameter update in deep excavations of soft and highly anisotropic soils, with the Mohr-Coulomb constitutive model and compared with an advanced soil model, MIT-E3 (Whittle & Kavvadas, 1994). This methodology overcomes the existing limitations by including sensitivity analysis to determine the parameters to be updated, combines different types of instruments in the inverse analysis (through the covariance matrix, including the coupling of the residuals) and uses evolutionary optimization methods (genetic algorithm).

In the specific case of the tailings deposit under study, it is instrumented with piezometers and prisms. This allows updating the parameters using advanced constitutive models, which by combining both measurements and using the genetic algorithm as an optimization method, more accurate predictions are obtained about the behavior of the deposit.

2 UPDATING METHODOLOGY

The parameter updating methodology consists of a series of iterative steps, whose flow diagram is shown in Figure 1. It starts with the site investigation, which collects all the information necessary to generate the numerical model, including aspects such as geometry, stratigraphy and data from in-situ and laboratory tests. With this information, the numerical model is developed together with the construction sequence, which allows obtaining initial predictions (p).

As the project progresses, new information is collected on the actual construction conditions, comparing them with the initial design conditions. This feedback is essential to reduce the uncertainty in the models and can be used continuously throughout the project. Once the in-situ instrumentation is available, the field monitoring process is initiated to obtain the measurements (m) used in the parameter update methodology.

With the initial predictions and the measurements, two key parameters proposed by Corral (2013) are calculated: the Structured Square Residual (SSR) and the Structured Global Variance (SGV), explained in section 2.2. Then the Sensitivity Analysis is performed to identify the parameters of the constitutive models and/or variables to be updated, followed by the Inverse Analysis to obtain the updated variables within the numerical models, thus allowing an accurate update of the model and a more accurate prediction.

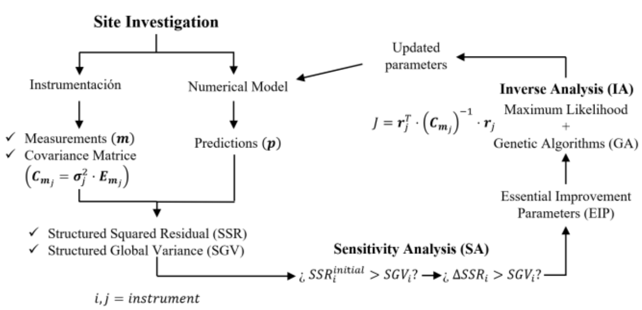

Figure 1. Simplified parameter updating procedure (after Corral 2013)

In summary, this methodology integrates information from the site investigation, the numerical model and the geotechnical monitoring through the sensitivity and inverse analysis to improve the predictions in geotechnical engineering.

2.1 Covariance Matrix and Error Structure

To apply this methodology, it is necessary to estimate the covariance matrix and the error structure in each instrument used in the project. The covariance of the measurements is constant in each time interval, which allows applying the maximum likelihood approach to the minimization problem. Under the assumption of having t independent instruments, the maximum likelihood can be expressed in terms of independent covariance matrices through the following equation (Ledesma et al., 1996; and later extended by Corral, 2013):

$$J = \sum_j^t \left[\boldsymbol{r}_j^T \cdot \left(\boldsymbol{C}_{\boldsymbol{m}_j} \right)^{-1} \cdot \boldsymbol{r}_j \right] \tag{1}$$

Where J represents the maximum likelihood, $\boldsymbol{C}_{\boldsymbol{m}_j}$ is the covariance matrix of each instrument $\boldsymbol{j}$, and $\boldsymbol{r}_j$ represents the residual vector of each instrument $\boldsymbol{j}$, defined as $\boldsymbol{r} = \boldsymbol{m} - \boldsymbol{p}$.

The covariance matrix is estimated as:

$$\boldsymbol{C}_{\boldsymbol{m}_j} = \boldsymbol{\sigma}_j^2 \cdot \boldsymbol{E}_{\boldsymbol{m}_j} \tag{2}$$

Where $\boldsymbol{\sigma}_j^2$ is a scalar factor that represents the global variance of the instrument j and $\boldsymbol{E}_{\boldsymbol{m}_j}$ corresponds to the error structure of each instrument j, which depends on the device itself.

The main drawback of using the expression of Equation 1 is that combining different instrumentation types with different units is not apparently possible. Therefore, Corral (2013) developed some key dimensionless expressions for the error structure matrices (e.g. inclinometers)

This work focused on pointwise instrumentation.

2.1.1 *Pointwise Instruments*

The point instruments measure a physical parameter at a single independent point, where the errors associated with these measurements are attributed to random errors. In this context, the error structure $\boldsymbol{E}_{\boldsymbol{m}_j}$ is defined by the identity matrix and the covariance matrix opts for its simplest form:

$$C_{m_j} = \sigma_j^2$$
$$\sigma_j^2 = \frac{1}{N_j} \cdot \sum_j^t (x_i - \bar{x})_j^2 \tag{3}$$

Where σ_j^2 represents the population variance of the instrument j in a specific construction stage, N_j is the number of measurements of the instrument j, x_i is each of the individual measurements, and $\bar{x}$ is the arithmetic average of the N_j measures.

Finally, the covariance matrix in the point instruments is represented as a diagonal matrix of the variances of each of the point instruments in a time interval or construction stage. The time interval or construction stage plays a key role in the calculation of the variance due to two reasons: (i) the numerical predictions imply a temporal discretization in a continuous process, so it is necessary to integrate a realistic time interval to accurately reflect the measurements, and (ii) the number of data measured in the time interval must be sufficient to obtain a valid estimate with realistic variances. Otherwise, the measurement should not be included during the update process.

2.2 Structured Square Residual (SSR) and Structured Global Variance (SGV)

This step is responsible for calculating the filters necessary to carry out the sensitivity analysis. These filters need to calculate the scalar values of SSR and SGV for each instrument type. Corral (2013) proposed to write these expressions as follows:

$$SSR_i = \boldsymbol{r}_i^T \cdot \boldsymbol{E}_{\boldsymbol{m}_i}^{-1} \cdot \boldsymbol{r}_i \tag{4}$$

$$SGV_i = \boldsymbol{\sigma}_i^T \cdot \boldsymbol{E}_{\boldsymbol{m}_i}^{-1} \cdot \boldsymbol{\sigma}_i \tag{5}$$

These values are calculated for each of the instruments i and are used for the filters in the sensitivity analysis, in order to determine the parameters that require to be considered within the optimization (inverse analysis).

2.3 Sensitivity Analysis (SA)

This analysis has three main objectives: (i) to identify the most relevant parameters of the model, necessary in the optimization process; (ii) to identify the instruments or types of measurements that provide more information for the inverse problem; and (iii) to quantify how much the SSR can be reduced by varying a single parameter (Corral, 2013).

The sensitivity analysis comprises two filters to determine whether a parameter needs to be optimized:

The first filter help one to evaluate whether or not the SSR with the initial parameters of the model is greater than the SGV of the instrumentation, allowing to know if the parameter has a possible improvement within the inverse analysis. A residual is considered essential when the absolute value of the initial residual exceeds the standard deviation of the instrumentation $\left(SSR_i^{inicial} > SGV_i\right)$, while a residual is considered as non-essential when it does not exceed that value. the second filter, the ΔSSR_i is required to be calculated which corresponds to the maximum reduction of the SSR_i in relation to the initial parameters of the model in each of the instruments i.

$$\Delta SSR_i = SSR_i^{inicial} - SSR_i^{min} \quad (6)$$

Where SSR_i^{min} is the minimum value of the structured square residual obtained in each of the instruments i when evaluating a range of parameters.

The value of ΔSSR_i is evaluated for each of the parameters and, if $\Delta SSR_i > SGV_i$ it is called "Essential Improvement Parameter" (EIP), which indicates that this parameter must be considered in the optimization process in the inverse analysis.

2.4 Inverse Analysis (IA)

The inverse analysis introduced by Corral (2013) uses the maximum likelihood approach as an identification criterion and uses the genetic algorithm as an optimization method. Once the covariance matrices have been defined in each of the instruments and the EIPs have been identified, the formulation of the maximum likelihood approach is presented as follows:

$$min\{J\} = min\{\boldsymbol{r}^T \cdot (\boldsymbol{C_m})^{-1} \cdot \boldsymbol{r}\} \quad (7)$$

It is essential to highlight that the maximum likelihood analysis considers all the measurements, regardless of the results of the sensitivity analysis. This implies that, although the sensitivity analysis indicates the elements that require improvement, the minimization (optimization) problem considers all the instruments. The proper configuration of the genetic algorithm plays a crucial role in achieving a good approximation in obtaining the local minima.

Subsequently, to quantify the improvement obtained after the inverse analysis, an incremental improvement ratio is used in relation to the initial value of J.

3 CASE STUDY

The study focuses on the analysis of a tailings dam located in South America, with a storage capacity that exceeds 400 billion tons of fine tailings. The dam was built using borrow material from quarries near the site. To ensure the stability and impermeability of the dam, a waterproof geosynthetic was installed on the upstream face. In addition, a drainage system was installed at the base to capture and channel possible seepage from water and precipitation.

The dam was modeled in Plaxis 2D and consists of 4 stages. As the height of the dam increases, so does the height of the tailings, maintaining a setback of 5 m according to the project guidelines. The geometry of the dam is detailed in Table 1.

Table 1. Geometry of the tailings dam

Stages	**Slopes** Upstream $[\boldsymbol{H}:\boldsymbol{V}]$	Downstream $[\boldsymbol{H}:\boldsymbol{V}]$	**Crest width** $[\boldsymbol{m}]$	**Average height** $[\boldsymbol{m}]$
Starting Wall	1,8: 1	1,8: 1	53	139
Stage 1	1,5: 1	1,8: 1	50	154
Stage 2	1,5: 1	1,9: 1	50	170

The model considers five types of soils: Rock, Alluvial, Drain, Wall, and Tailings. The maximum dimensions of the model are $2.550m$ in the $x-$ axis and $436{,}9m$ in the $y-$ axis. Four points were in the model that represent the prisms (Pr) and piezometers (P-1, P-2, and P-3) located above the Drain material. All the details of the model are shown in Figure 2.

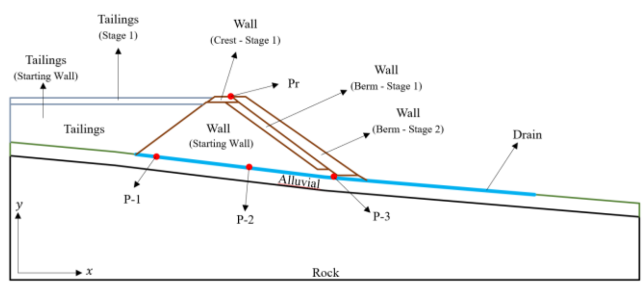

Figure 2. Geometry and construction stages of the tailings dam

3.1 Constitutive Models

Soil/rock properties and parameters were estimated from field and laboratory tests to model the behavior of the five materials present in the model. The dam, alluvial and drain were modeled using the Hardening Soil small Strain (HS small) model, the tailings using the Hardening Soil (HS) model and the rock using the Linear Elastic (LE) model.

Four alternative variables were defined within the models previously well-defined in (Bentley, 2021a). Within the HS small and HS constitutive models, the variables α and β are defined, where a correlation is established between the parameter E_{50}^{ref} and the parameters E_{oed}^{ref} and E_{ur}^{ref}:

$$E_{oed}^{ref} = \alpha \cdot E_{50}^{ref} \quad (8)$$
$$E_{ur}^{ref} = \beta \cdot E_{50}^{ref} \quad (9)$$

The variable Ω is an alternative measure that represents the minimum stiffness reduction in the HS small model.

$$G_0^{ref} = G/\Omega \tag{10}$$

Finally, κ establishes a correlation between the permeabilities in the x and y directions.

$$\kappa = k_x/k_y \tag{11}$$

The initial values of the parameters in the constitutive models are shown in the Table 2, where the parameters considered with uncertainty, subject to sensitivity analysis, are highlighted.

Table 2. Initial values of the parameters in the constitutive models

Materials		Wall	Alluvial	Drain	Tailings	Rock
Constitutive Model		HS small			HS	LE
Drainage type		Drained				
γ_d	$[kN/m^3]$	20	18,4		12,3	24,1
γ_{sat}	$[kN/m^3]$	22	19,6		18	24,1
E'	$[MPa]$	–	–	–	–	$1,0 \cdot 10^4$
ν'	$[-]$	–	–	–	–	0,35
OCR	$[-]$	1	1		1	–
E_{50}^{ref}	$[MPa]$	40	40		4	–
α	$[-]$	1	1		1	–
β	$[-]$	3	3		3	–
m	$[-]$	0.5	0.5		0,5	–
c'	$[kPa]$	5	5		0	–
φ'	[°]	38	38		31	–
ψ	[°]	0				–
ν'_{ur}	$[-]$	0,2				–
R_f	$[-]$	0,9				–
p_{ref}	$[kPa]$	100				–
$\gamma_{0.7}$	$[-]$	$3,0 \cdot 10^{-5}$	$3,0 \cdot 10^{-5}$		–	–
Ω	[%]	10	10		–	–
k_x	$[m/s]$	$4,0 \cdot 10^{-5}$	$1,0 \cdot 10^{-5}$	$1,0 \cdot 10^{-4}$	$1,0 \cdot 10^{-7}$	$5,0 \cdot 10^{-7}$
κ	$[-]$	1	1	1	1	1

Although it is not included in the Table 2, the van Genuchten model is also used in the Wall, since this material presents saturated, partially saturated, and dry zones. The parameters established in the model correspond to a standard data set of a coarse material, as indicated in (Bentley, 2021b).

3.2 Finite Element Model (FEM)

The model consists of five fundamental stages, which correspond to the construction stages of the tailings dam in the field. To adequately simulate the construction process, the model is divided into 69 phases, which are subdivisions of the construction stages of the deposit used in the numerical model to properly represent its behavior and are detailed in Gavidia (2023).

Within the assumptions of the model, the following is considered:

- A waterproof interface is established on the upstream slope to simulate the presence of the membrane installed in the tailings dam, to prevent seepage in the wall.
- The fine tailings are deposited hydraulically, therefore, conservatively it is assumed that the tailings are always saturated.
- At the end of the construction of the drain, there is a weir, where a constant water extraction flow of $0,02\,m^3/s/m$ is considered.

3.3 Monitoring in tailings dam

The studied tailings dam is equipped with prisms and piezometers (pointwise instruments), which enable the obtaining of information about the behavior of the materials as the construction progresses. This allows obtaining all the corresponding measures necessary for the calculation of the covariance matrix and the comparisons with the initial predictions using the parameters obtained from tests.

3.3.1 *Prims*

The recording of the prisms was carried out during the construction of Stage 2 of the wall, which lasted approximately 435 days. During this process, 9 prisms were installed on the crown of Stage 1, which provided detailed information on the settlement and transverse deformation as the construction of the backfill of Stage 2 progressed. Continuous monitoring was carried out over a period of 137 days, which coincided with the moment when the backfill of Stage 2 reached the same elevation as the crown of Stage 1.

The data are broken down monthly to facilitate comparison with the numerical model and are divided into 5 months to represent the periods in which the monitoring information was collected, where month 5 is half a month and therefore small deformations can be observed in both directions, it is relevant to mention that at least one data per hour was recorded.

Figure 3 presents the data averaged and broken down monthly to facilitate comparison with the numerical model, they are presented in more details by Gavidia (2023). In addition, the standard deviation is included as a measure of variability of these magnitudes, which allows the fluctuations in the deformation values to be visually appreciated. These results allow us to validate and adjust the finite element model used in the study.

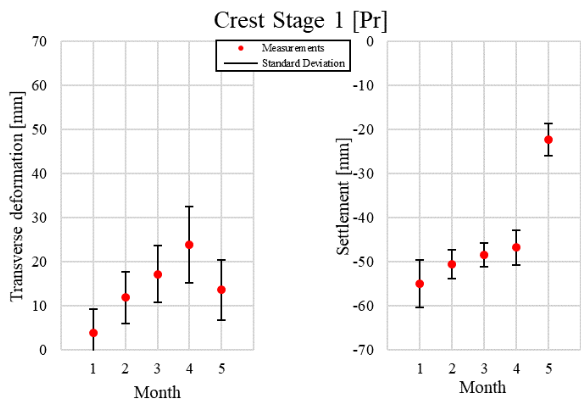

Figure 3. Measurements and standard deviations of the prisms: (a) Transverse deformations and (b) Settlements

3.3.2 *Piezometers*

A set of five vibrating string piezometers located near the analyzed section of the wall was considered. These piezometers provided detailed information on the pore pressures from the construction of the crown and slimes of Stage 1 until the development of the construction of the backfill of Stage 2. Continuous monitoring of the piezometers in the tailings dam was carried out over a period of 501 days, coinciding in the moment when the backfill of Stage 2 reached the same elevation as the crown of Stage 1.

The average data are divided into two categories: the initial pore pressure and the growth of the pore pressure experienced by each piezometer after 501 days.

Figure 4 illustrates the average measurements of both categories, as well as the standard deviation as a measure of variability of these magnitudes. The details of each of these data are presented by Gavidia (2023). It is important to mention that the pore pressures in the table change sign due to the sign convention used by the PLAXIS software.

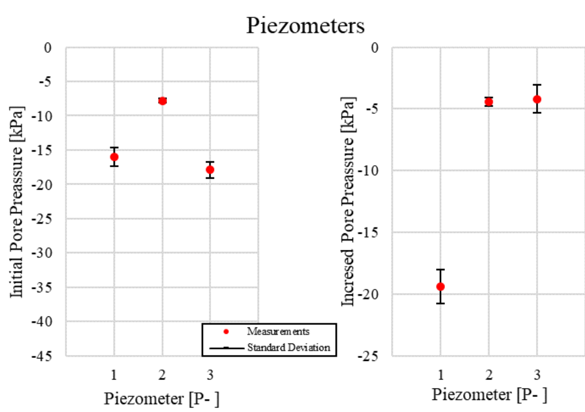

Figure 4. Measurements and standard deviations of the piezometers: (a) Initial pore pressure and (b) Growth of pore pressures in 501 days

3.4 *Sensitivity Analysis*

The two criteria or filters explained above were applied. In the first one, it was evaluated if $SSR_i^{inicial} > SGV_i$. It was observed that all the $SSR_i^{inicial}$ are greater than the SGV_i, which indicates that none of the predicted values are within the range of the standard deviation of the monitoring, as can be seen in Figure 5 and Figure 6.

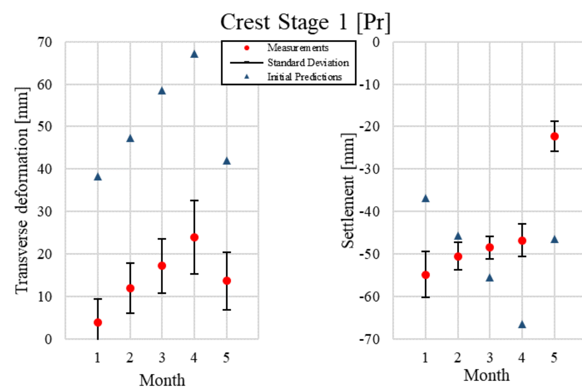

Figure 5. Comparison in the prisms: (a) Transverse deformations and (b) Settlements, between measurements and initial predictions

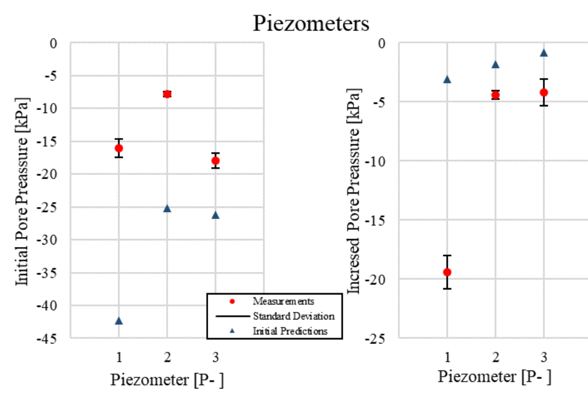

Figure 6. Comparison in the piezometers: (a) Initial pore pressure and (b) Growth of pore pressures in 501 days, between measurements and initial prediction

This implies that all the instrumentation points considered must be evaluated in the second criterion of the sensitivity analysis, which evaluates ΔSSR_i since all the parameters are EIP. The search space established for each of the parameters is set considering the recommendations of Ameratunga et al. (2016) based on the coefficients of variation.

Table 3. Search space of the parameters

Material	Parameters [Unidad]	Limit Lower	Limit Upper
Wall	$\gamma_d\ [kN/m^3]$	$\gamma_d - 2$	$\gamma_d + 2$
	$\gamma_{sat}\ [kN/m^3]$	$\gamma_{sat} - 2$	$\gamma_{sat} + 2$
	$OCR\ [-]$	1	3
	$E_{50}^{ref}\ [MPa]$	$E_{50}^{ref}/4$	$4 \cdot E_{50}^{ref}$
	$\varphi'\ [°]$	$\varphi' - 6$	$\varphi' + 8$
	$\gamma_{0.7}\ [-]$	$1 \cdot 10^{-5}$	$1 \cdot 10^{-4}$
	$\Omega\ [\%]$	$\Omega - 3$	$\Omega + 3$
	$k_x\ [m/s]$	$8 \cdot 10^{-6}$	$7{,}2 \cdot 10^{-5}$
	$\kappa\ [-]$	$\kappa/4$	$4 \cdot \kappa$
Alluvial	$E_{50}^{ref}\ [MPa]$	$E_{50}^{ref}/4$	$4 \cdot E_{50}^{ref}$
	$\varphi'\ [°]$	$\varphi' - 6$	$\varphi' + 8$
	$k_x\ [m/s]$	$1 \cdot 10^{-6}$	$2 \cdot 10^{-5}$
	$\kappa\ [-]$	$\kappa/4$	$4 \cdot \kappa$
Rock	$k_x\ [m/s]$	$5 \cdot 10^{-8}$	$1 \cdot 10^{-6}$
	$\kappa\ [-]$	$\kappa/4$	$4 \cdot \kappa$
Drain	$k_x\ [m/s]$	$1 \cdot 10^{-5}$	$2 \cdot 10^{-4}$
	$\kappa\ [-]$	$\kappa/4$	$4 \cdot \kappa$
Tailings	$E_{50}^{ref}\ [MPa]$	$E_{50}^{ref}/4$	$4 \cdot E_{50}^{ref}$
	$\varphi'\ [°]$	$\varphi' - 7$	$\varphi' + 9$
	$k_x\ [m/s]$	$1 \cdot 10^{-8}$	$2 \cdot 10^{-7}$
	$\kappa\ [-]$	$\kappa/4$	$4 \cdot \kappa$

All details of the current analyses are described by Gavidia (2023) and it was observed that in all cases the value of ΔSSR_i is greater than its SGV_i. However, due to the high computational cost associated to the inverse analysis of the 21 parameters, it is decided to reduce the number of parameters and assign them a categorization according to their importance in the overall improvement of the prediction. In this way, an average of the results obtained from the set of instruments evaluated, which include prisms and piezometers, is calculated. This average is represented as the Structured Mean Squared Residual Improvement (SMSRI).

$$SMSRI = \frac{\sum \frac{\left(SSR_i - SSR_i^{inicial}\right)}{SGV_i}}{n} \tag{12}$$

Where n is the total number of point instruments $(n = 16)$. Therefore, if $SMSRI < 0$, it indicates an average improvement of the structured quadratic residual, which allows to categorize each of the parameters considered with uncertainty according to their relevance to improve the prediction.

Table 4 shows the first 11 parameters from the $SMSRI_{min}$. These will be considered for the inverse analysis, ensuring that more than half of the parameters initially considered as EIP are included, which guarantees a wide coverage of parameters in the inverse analysis.

Table 4. Order of importance of the first 11 parameters according to the SMSRI in the model

Order	Parameters	$SMSRI_{min}$
1	k_x – Drain	$-2.790{,}4$
2	k_x – Alluvial	$-2.746{,}8$
3	k_x – Rock	$-2.708{,}8$
4	κ – Tailings	$-2.611{,}7$
5	k_x – Tailings	$-1.935{,}9$
6	k_x – Wall	$-1.712{,}1$
7	κ – Wall	$-289{,}9$
8	κ – Rock	$-212{,}7$
9	E_{50} – Wall	$-122{,}0$
10	$\gamma_{0.7}$ – Wall	$-98{,}8$
11	E_{50} – Tailings	$-95{,}4$

3.5 *Inverse Analysis*

Within this methodology, the genetic algorithm is used as an optimization method through the MATLAB software. The interaction between MATLAB and PLAXIS 2D is done through Python, allowing the connection of two widely known commercial software using one of the most widely used programming languages worldwide.

For the development of the methodology, certain control parameters of the genetic algorithm were established, which include the population size, parent selection, crossover, mutation and stop criterion. A population size of 8 individuals per each EIP is defined, which generates a population of 88 individuals. A migration of 20% of the population was carried out, where the parents represent 10% and an elitist selection criterion was used. A random crossover fraction of 80% was applied. In addition, a mutation function was implemented that introduces small random changes in the individuals of the population, which contributes genetic diversity and allows the genetic algorithm to explore a wider space of solutions.

As a stop criterion of the genetic algorithm, it is established that Δ_{STOP} must maintain a percentage difference lower than 3% for three consecutive generations.

$$\Delta_{STOP} = \frac{J_{Parents}^{ave} - J_{Total}^{min}}{J_{Parents}^{ave}} \cdot 100[\%] \tag{13}$$

Δ_{STOP} represents the percentage difference between the average of the parents of the total objective function $(J_{Parents}^{ave})$ and the minimum value of the total objective function (J_{Total}^{min}). In this case study, the stop criterion is achieved in generation 12.

The convergence of the total objective function is presented in Figure 7 for the combination of all the instruments. It is important to highlight that the blue line represents the value obtained with the initial parameters $(J_{Total}^{ini} = 3{,}329)$, while the green line represents the value J_{Total}^{min} in generation $(J_{Total-12}^{min} = 195)$. The J_{Total}^{min} does not imply that it is the lowest value of J for each of the instruments, since, if an inverse analysis were performed with the instruments independently, a different parameter combination would be obtained for each instrument. However, as the generations pass, the methodology tends to obtain the lowest values of J in each one.

Table 5 summarizes the search limits established for each of the parameters during the inverse analysis and the updated parameters at the end of generation 12.

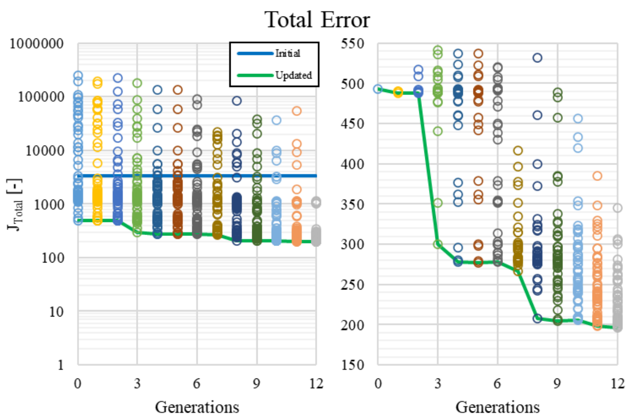

Figure 7. Convergence of the objective function for all the measures

Table 5. Search limits and updated parameters obtained from the IA

Parameters	Lower limit	Upper limit	Updated parameter
k_x **Drain** $[m/s]$	$1 \cdot 10^{-5}$	$2 \cdot 10^{-4}$	$4{,}7 \cdot 10^{-5}$
k_x **Alluvial** $[m/s]$	$1 \cdot 10^{-6}$	$2 \cdot 10^{-5}$	$8{,}4 \cdot 10^{-6}$
k_x **Rock** $[m/s]$	$5 \cdot 10^{-8}$	$1 \cdot 10^{-6}$	$5{,}1 \cdot 10^{-7}$
κ **Tailings** $[-]$	0,25	4,00	1,87
k_x **Tailings** $[m/s]$	$1 \cdot 10^{-8}$	$2 \cdot 10^{-7}$	$1{,}1 \cdot 10^{-7}$
k_x **Wall** $[m/s]$	$8 \cdot 10^{-6}$	$7{,}2 \cdot 10^{-5}$	$2{,}5 \cdot 10^{-5}$
κ **Wall** $[-]$	0,25	4,00	3,06
κ **Rock** $[-]$	0,25	4,00	0,56
E_{50} **Wall** $[MPa]$	1	160	60,3
$\gamma_{0.7}$ **Wall** $[-]$	$1 \cdot 10^{-5}$	$1 \cdot 10^{-4}$	$5{,}4 \cdot 10^{-5}$
E_{50} **Tailings** $[MPa]$	1	16	1,2

Figure 8 and Figure 9 show the results of the predictions obtained with the updated parameters, demonstrating that this methodology presents a general improvement of the predictions compared to those obtained with the initial parameters. In general, an improvement is observed in thirteen of the sixteen points evaluated, which demonstrates that by reducing the uncertainty in the model including the information from the monitoring of the works, more accurate predictions of a numerical model are obtained.

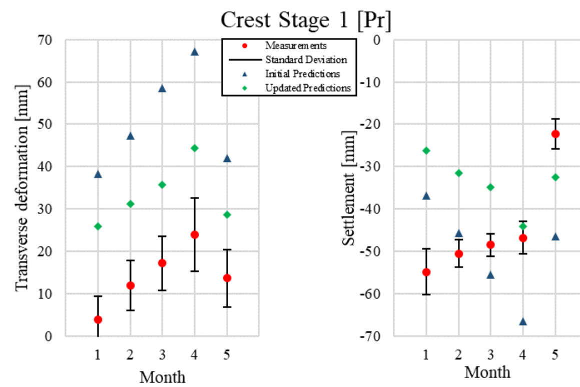

Figure 8. Comparison in the prisms: (a) Transverse deformations and (b) Settlements, between measurements and initial predictions

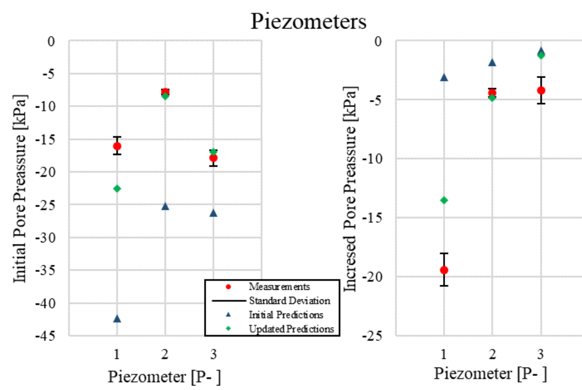

Figure 9. Comparison in the piezometers: (a) Initial pore pressure and (b) Growth of pore pressures in 501 days, between measurements and initial predictions

4 CONCLUSIONS

This paper has demonstrated the effectiveness of the applied methodology to implement the observational method proposed by Peck (1969), which provides the ability to adjust the design and improve the predictions more reliably, reducing the uncertainty and increasing the safety of geotechnical works. This approach has the potential to decrease future costs related to repairs and maintenance, by providing a more accurate assessment of the site conditions.

A significant improvement in the predictions of deformations and pore pressures was observed in 4 points of the tailings dam, reaching an improvement ratio of 94% compared to the initial predictions. These results give the designers more confidence to evaluate the next construction stage and adjust in the design as needed.

The use of genetic algorithms was highlighted as a highly effective optimization method, as it allows the independent evolution of the parameters and an exhaustive search in the solution space. Its ability to introduce random changes and explore a wider range without relying solely on engineering experience adds diversity to the optimization process.

It is important to highlight that that parameter updating should occur collectively rather than individually. This is because the updated parameters do not always directly correlate with the minimum value attained in the Average Structured Square Residual Improvement. Therefore, it is essential to recognize the interaction and interdependence among parameters to achieve more accurate and reliable results in geotechnical analyses.

To sum up, the proposed methodology brings about: (1) improved safety measures leading to safer predictions; (2) flexibility to employ the observational method, enabling adaptable designs; (3) effective management of construction schedules to avoid delays; and (4) decreased construction expenses by potentially switching to less expensive options when the original design permits modification.

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