Selecting time series models for predicting concrete dam foundation uplift pressure ⋆

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Abstract: The level of piezometric pressure at the concrete-rock interface and at discontinuities in the foundation of a concrete dam has a great influence on overturning movements. The objective of this study was the selection of models for the prediction of uplift pressures in the foundation of a concrete dam on the basis of historical time series values only. The models were automatically modeled using the fests package in the R software. The models were evaluated on the basis of RMSE. All of them satisfactorily represented the time series profile of the monthly averages of the measurements of six piezometers of the Itaipu Dam and were able to predict the long-term underpressures with reasonable accuracy. The results obtained indicate that the automation of the modeling can assist in the monitoring and follow-up of the evolution of the behavior of the dam in its current phase.

Keywords: Autoregressive integrated moving average; Exponential smoothing state space; Feed-forward neural network autoregression; Vector autoregression; Dam monitoring; Piezometer.

1. INTRODUCTION

Monitoring a system in real time is often challenging because of the characteristics of the data. In this regard, knowing the statistical characteristics of each data set allows appropriate statistical models to provide representations of its behavior over time and then support the decision making process. Similarly, the performance of predicting the data of the monitored system according to different time windows, such as short, medium, or long term, depends on predictive models that produce estimates similar to the pattern identified in the data.

The modeling of data from instruments used in structural monitoring of dams has been the subject of several recent studies. The choice of approaches and techniques varies according to the intrinsic characteristics of the data. The periodicity of displacements measured by inverted pendulums was analyzed by Gamse et al. (2020) using hydrostatic seasonal time models. Lazzarotto et al. (2015), applied wavelet decomposition and used hybrid autoregressive integrated moving average (ARIMA) generalized autoregressive conditional heteroskedasticity models linearly combined with artificial neural networks (ANNs) to obtain predictions of displacements measured by a direct pendulum. Pereira et al. (2016) analyzed in different domains the displacements measured by a direct pendulum installed in a key block of a relieved gravity dam, distinguishing less subtle and more refined time series characteristics and improving the predictions with a methodology composed of wavelet decomposition and hybrid ANNs models. Hua et al. (2023) combined the feature extraction capabilities of convolutional neural networks in deep learning with the long-term memory structure characteristics of gated recurrent neural networks to predict the subsidence at the foundation of a concrete dam. Time series of piezometer measurements were also used by Pereira et al. (2021) to propose a probabilistic model for predicting subsidence.

Considering the data produced by these sensors, they are featured as a time series once they are presented over time. Therefore, analyzing and forecasting these data play a crucial role in dam monitoring. Once adjusting a suitable

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model that learns the data behavior and provides forecasting allows the analysts to establish trends, detect periodicities, and will enable the prediction of their temporal evolution with statistical reliability. Such kind of analysis plays a fundamental role once it allows identifying possible changes in the behavior of structures. Also, it will enable the specialist to quickly detect, evaluate and manage actions as preventive or corrective measures provided when necessary. Therefore, the objective of this study was the selection of models for the prediction of uplift pressures in the foundation of a concrete dam on the basis of historical time series values only.

The remainder of this article is organized as follows. Section 2 presents the theoretical aspects of time series models. Dam monitoring is described in Section 3. Section 4 describes the application and results. Finally, Section 5 presents the conclusion and future research.

2. TIME SERIES MODELING

A time series is a set of observations ordered over time, where $y_t \in R$, in which t is the instant where the value of y is recorded. The time series analysis is focused on the study of the time or frequency, where parametric and non-parametric models can be adopted, respectively (Morettin and Toloi, 2006). The initial steps of the time series modeling aim to analyze the behavior of the data, where tendency, seasonality, and cyclicity can be identified. From this point, the data modeling must follow some steps to accommodate these characteristics, such as problem definition, gathering the information, exploratory data analysis, selection of forecasting models, and models' performance evaluation (Athanasopoulos and Hyndman, 2021). In this Section, the forecasting models used in this study are detailed as follows.

2.1 Autoregressive integrated moving average model

An ARIMA model is the combination of two well established approaches. The first one is related to autoregressive factors (AR) and the second to moving averages (MA). Both approaches are joined by the integration part, indicated by "I" in the ARIMA method. This approach, where no seasonal factors are taken into account by the modeling, is presented as ARIMA(p, d, q), where $p, d, q \in N$ are the parameters that describe the model. Indeed, p is related to the number of lagged values for the AR model, d defines the differentiation order (operator related to the stationarity of the process), and q is the MA order. Once the data have a seasonal behavior, the model can be written as ARIMA$(p, d, q)(P, D, Q)_m$ where P, D, Q, and m are related to the autoregressive, differentiation, moving average, and seasonal period of the data. From a broader perspective, an ARIMA(p, d, q) can be written as follows:

$$\Phi_p(B)(1-B)^d Y_i^1 = \Theta_q(B)\epsilon_t \quad (1)$$

where $\Phi_p(B) = 1-\sum_{i=1}^{p} \varphi_i B^i$ and $\Theta_q(B) = 1-\sum_{j=1}^{q} \theta_j B^j$, φ_i and θ_i are parameters to be estimated, B is the backshift operator, and $\epsilon_t \sim iid(0, \sigma^2)$. Further details are presented in Box et al. (2015).

2.2 Exponential smoothing state space model

An exponential smoothing state space model (ETS) is an approach proposed over the last seventy years. According to Hyndman and Khandakar (2008), an ETS method is an algorithm that provides point forecasts. On the other hand, a state space model provides the same point forecasts and computing prediction intervals. Indeed, this kind of forecasting approach has three letters to be defined. The first denotes the error type; the second indicates the trend type; and the third represents the season type (Hyndman and Khandakar, 2008).

The general formulation of the state space model is similar for all the 30 ETS variations. Indeed, the general model involves a state vector

$$\boldsymbol{x}_t = (l_t, b_t, s_t, s_{t-1}, \dots, s_{t-m+1})' \quad (2)$$

where

$$y_t = w(\boldsymbol{x}_{t-1}) + r(\boldsymbol{x}_{t-1})\epsilon_t \quad (3)$$

$$\boldsymbol{x}_t = f(\boldsymbol{x}_{t-1}) + g(\boldsymbol{x}_{t-1})\epsilon_t \quad (4)$$

where $\epsilon_t \sim iid(0, \sigma^2)$, $\mu_t = w(\boldsymbol{x}_{t-1})$, and all components of $\boldsymbol{x}_t$ are parameters of each version of ETS model. All the ETS models can be written in the form presented by 3 and 4. Provides further details Hyndman and Khandakar (2008).

2.3 Feed-forward neural network autoregression model

The ANNs are mathematical models that simulate biological neuron behavior and acquire knowledge through experience. According to Haykin (2009), an ANNs is a massively parallel distributed processor made up of simple processing neurons with a natural tendency to store experiential knowledge and make it available for use. In the field of time series forecasting, it is possible to consider that ANNs are efficient and reliable black-box models that deal with several temporal data features, such as nonlinearities and noise of the time series signal. ANNs are composed of a neuron model (information processing unit), an architecture (set of neurons interconnected and with some weights), and a learning algorithm (used to train the ANNs).

From a broader perspective, a feed-forward neural network is a kind of single-layer perceptron. A sequence of inputs enter the layer (lagged values for time series) and are multiplied by the weights in this model Haykin (2009). The weighted input values are then integrated to obtain the final forecast. This study uses the implementation of Hyndman and Khandakar (2008). These authors proposed to use for time series forecasting feed-forward neural networks with a single hidden layer and lagged inputs. The model is fitted with lagged values of y as inputs and a single hidden layer with size nodes. The inputs are for lags 1 to p and lags m to mP, where m is the time series frequency. Provides further details Aljaaf et al. (2021).

2.4 Vector autoregression model

A vector autoregression (VAR) forecasting model is featured as a multivariate approach. It deals with time series forecasting problems when two or more time series influence each other. In this approach, the target variable is handled as a function of the lagged values of the original data, for example. It is an approach similar to Box & Jenkins models. However, it is bi-directional modeling; once lagged values, variables influence the future.

According to Athanasopoulos and Hyndman (2021), suppose that we have $Y_1(t)$ and $Y_2(t)$, and it is desired to forecast both variables over time. In this case, both lagged values for each one will be used as predictors. Then, a p-order VAR model can be written as follows,

$$
\begin{aligned}
Y_{1,t} = \alpha_1 + &\beta_{11,1}Y_{1,t-1} + \beta_{12,1}Y_{2,t-1} + \\
&\beta_{11,2}Y_{1,t-2} + \beta_{12,2}Y_{2,t-2} + \ldots + \\
&\beta_{11,p}Y_{1,t-p} + \beta_{12,p}Y_{2,t-p} + \epsilon_{1,t} \qquad (5)\\
Y_{2,t} = \alpha_2 + &\beta_{21,1}Y_{1,t-1} + \beta_{22,1}Y_{2,t-1} + \\
&\beta_{21,2}Y_{1,t-2} + \beta_{22,2}Y_{2,t-2} + \ldots + \\
&\beta_{21,p}Y_{1,t-p} + \beta_{22,p}Y_{2,t-p} + \epsilon_{2,t} \qquad (6)
\end{aligned}
$$

where $\epsilon_{i,t}$, $i = 1, 2$, are the white noise processes, $\beta_{ii,p}$ capture the influence of p-th lag value of Y_i on itself, while $\beta_{ij,p}$ capture the influence of p-th lag value of Y_j on Y_i. Once the number of time series in the model increases, the system of equations becomes larger.

2.5 Naïve method

The Naïve method is a simple forecasting approach, defined as the next forecast value equals the last observed value. The forecast values are equal to the last season for seasonal data (SNAÏVE). The mathematical structure for non-seasonal (7) and seasonal (8) approaches can be defined as follows,

$$\hat{y}_{T+h|T} = y_T \qquad (7)$$

$$\hat{y}_{T+h|T} = y_{T+h-m(k+1)} \qquad (8)$$

where where m is the seasonal period, k is the integer part of $(h-1)/m$.

2.6 Performance Measures

In order to evaluate the forecasting results for fitted and forecasted values, the root mean squared error (RMSE) is used is this study, and can be computed as follows,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (9)$$

where n is the number of observations, y_i and $\hat{y}_i$ are the i-th observed and forecasting values, respectively.

3. STRUCTURAL MONITORING OF DAMS

Dams are structures built to raise the water level of a river or create a reservoir for the accumulation of water or another fluid. These constructions maintain a cause-effect relationship with the environment in which they are located. Upon the occurrence of disturbance sources (causes), such as thermal variations, changes in upstream or downstream water levels, seismic tremors, vibrations, structural aging, among others, the structures and foundations respond (effects) through stresses, strains, and displacements.

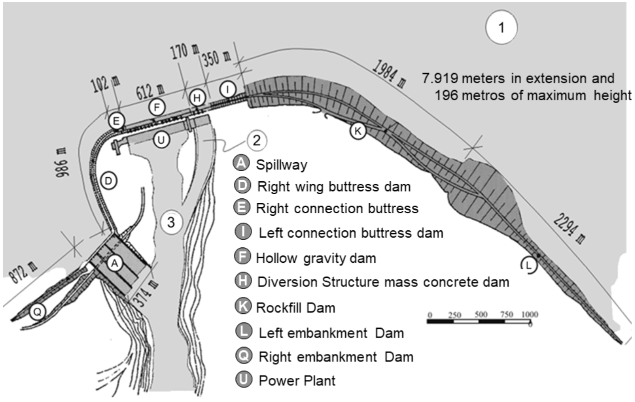

Figure 1. Itaipu Dam layout.
Source: ENCC (2019)

According to ICOLD (2018), the monitoring system and surveillance program should be planned and executed in a way that can quickly and accurately identify any abnormal behavior that may reduce structural safety. Auscultation is part of this monitoring system, with the instruments providing the data (quantitative) and the visual inspections of the observations (qualitative) of the dam's behavior, providing essential information for controlling its safety conditions, proving the validity of the assumptions and calculation methods used in the design, and verifying the need for corrective measures (Itaipu, 2023).

The number and variety of instruments used for structural monitoring depend on the size and type of dam (embankment, concrete, rockfill). For example, the Itaipu Hydroelectric Dam (Figure 1) has a comprehensive instrumentation program to monitor the behavior of all structures, consisting of approximately 2792 instruments, such as direct and inverted pendulums, triaxial extensometers, strain gauges, extensometers, thermometers, piezometers, among others (Itaipu, 2009). The information collected is periodically analyzed by a specialized team to identify possible anomalies and changes in structural behavior. This analysis is performed individually, by instrument type or by block, taking into account the historical and design values of the dam.

The uplift pressures, measured by piezometers, which are the focus of this study, alter the stress state of the rock mass foundation in a coupled hydromechanical process and can compromise the dam's stability (Pereira et al., 2021). According to Li et al. (2017), uplift pressures are influenced by several factors, such as reservoir level, temperature, rainfall, permeability coefficient, cracks, seepage control facilities, among others, which add nonlinear characteristics to the pressure trend.

The observation of these pressures is of utmost importance for the excellent supervision of safety conditions in a concrete dam, considering that the stability of its structures, concerning sliding, tumbling, or floating, is directly affected by the level of piezometric pressures at the concrete-

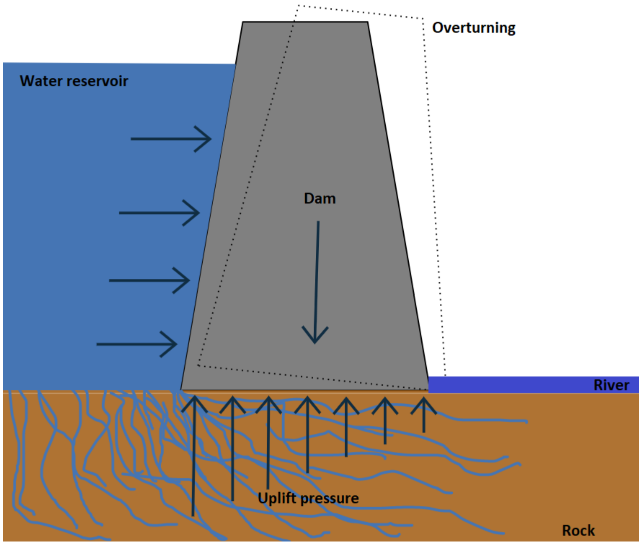

Figure 2. Overturning due to uplift pressure.

rock interface and in low-resistance sub-horizontal discontinuities existing in the foundation (Silveira, 2003).

The origin of these pressures can be simplified as follows: upstream of the dam is the reservoir and the river channel is far downstream. Physically, the difference in water levels creates a hydraulic gradient between upstream and downstream. The reservoir water flows mainly through the foundation massif and tries to pass downstream to reach hydraulic equilibrium (Bando, 2016). The infiltrating water pushes the dam from the bottom to the top; this force is called uplift pressure. In an extreme situation, in the absence of a drainage system and when the combination of the uplift and the hydrostatic pressure exerted by the reservoir (horizontal in the upstream-downstream direction) exceeds the resistance offered by the dam's weight, the structure may collapse, as shown in the Figure 2.

Therefore, measuring uplift pressures in the foundation of concrete dams is essential for supervising their safety conditions. Installing grout curtains and using a drainage system in the foundation of concrete dams are designed to minimize seepage and reduce uplift pressure.

According to Silveira (2003), significant increases in uplift may indicate the occurrence of clogging and blockage of foundation drains by solid particles carried by the drainage water, signaling the need to clean the drains or even drill new ones to ensure adequate stability conditions.

At the Itaipu Dam, the upstream uplift is equal to the reservoir level and at the downstream end can be considered equal to zero, for the blocks that are not in the riverbed and equal to the downstream level for the blocks in the riverbed region (with power station). The intermediate values depend on the seepage regime established in the foundations. The uplift acting can be verified in the pressures measured in the piezometers located in the foundations in the region of the concrete blocks. Since the beginning of the dam operation, the pressures measured by the piezometers have been systematically below design values, with many indicating stabilization or reduction of percolation (Itaipu, 2009).

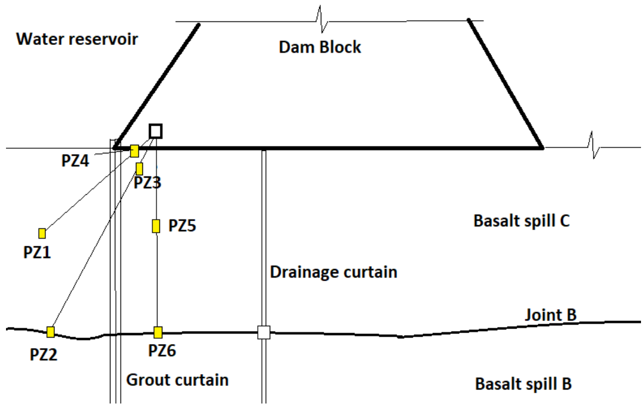

Figure 3. Location of the analyzed piezometers.

4. APPLICATION AND RESULTS

This is applied quantitative, descriptive, original, and field research since the knowledge applied to data from monitoring the Itaipu Dam's uplift pressures, located on the Paraná River, on the border between Brazil and Paraguay.

Firstly, the time series from the sensors of the Itaipu dam have been selected and their properties have been determined, such as seasonality, trends, linearity and autocorrelation in the observations. Next, the data are divided into two sets: training and validation. Models for time series analysis and forecasting are used from the training data, such as ARIMA and its seasonal version, ETS, VAR, and Feed Forward Artificial Neural Networks (NNAR). Random seasonal models (SNAÏVE) were also fitted for six instruments to compare the ability for time series forecasting tasks. Finally, the time window was thirty months forecast for the sensors using the best-fitting models based on RMSE criteria. Accuracy was evaluated by comparing the forecasting results with the validation set. The analyses and implementations were performed using the packages *fable* (O'Hara-Wild et al., 2022a), *feasts* (O'Hara-Wild et al., 2022b) and *forecast* (Hyndman and Khandakar, 2008) in the R software.

This study considered pressure data (in meters per water column - mWC) collected between January 1990 and June 2022 by six standpipe piezometers (represented by PZ1 to PZ6, Figure 3) installed in the foundation of one block of the main dam section. These instruments record, from the beginning of the dam's operation period, the piezometric heights of the foundation of this part of the dam, which presents flow conditions with increase or decrease of uplift pressure at the concrete-rock interface and geological features that condition the hydrogeological behavior of the massifs.

The following Figure 4 shows the evolution of the measurements of these piezometers. At first, it was noticed that the series showed different behaviors with changes in level (drift, PZ1 and PZ3), decreasing trends (PZ1 and PZ2), increasing trends (PZ4, PZ5 and PZ6), seasonality (PZ3 and PZ4), an increase in variability (PZ4) and outliers (PZ2 and PZ6).

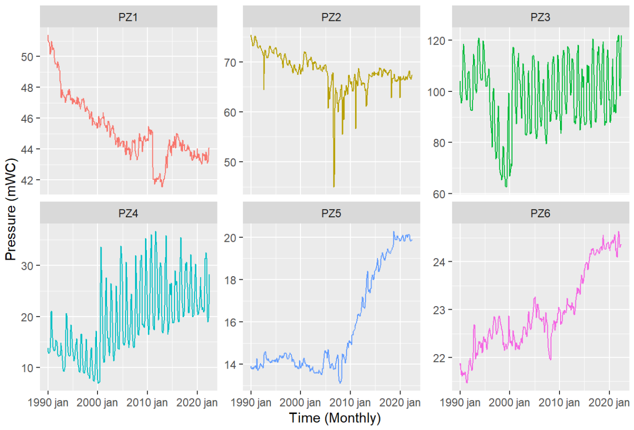

Figure 4. Measurements of uplifts collected by some piezometers at the Itaipu Dam.

All the analyzed series showed autocorrelation, indicating that present values depend on the past. Table 1 shows the fitted models for each piezometer and their respective error measures, ordered by those with the best quality of fit (lowest RMSE Fit). Seasonal ARIMA models were fitted for piezometers PZ3, PZ4, and PZ5. Piezometers PZ1, PZ4, PZ5, and PZ6, which presented sudden changes in values (jumps or steps), had this characteristic (*drift*) represented by ARIMA models. For piezometer PZ2, the integrated model of order one was fitted.

The adjusted ETS considered the peculiar characteristics of each instrument. Thus, the piezometer data were represented by the following simple exponential smoothing models with additive errors, without trend, and seasonality (PZ1 and PZ2); with additive errors, without trend, and with additive seasonality (PZ3); with multiplicative errors, without trend and with multiplicative seasonality (PZ4); with multiplicative errors, with the damped additive trend and with multiplicative seasonality (PZ5); with additive errors, with the damped additive trend and with additive seasonality (PZ6).

The NNAR represented the nonlinear relationships between observations, considering the seasonality of each time series with a lag. For piezometers PZ1, PZ5, and PZ6, the fitted models used a lag in the non-seasonal portion. The other instruments had many lags in this portion, with 15 for PZ2 and 25 for PZ3 and PZ4, indicating a greater long-term dependence.

The VAR, fitted using the ordinary least squares method, resulted in one, two, or five lags for the different instruments.

As, in general, the models had good fit quality in terms of RMSE, evaluated by the small magnitude of the errors, all of them were kept for the next stage of uplift pressure prediction for a thirty-month horizon. The accuracy of the forecasts was also evaluated through the RMSE, using the data set from January 2020 to June 2022.

The predictions obtained by the selected models in the training step generally resulted in values very close to those measured by the piezometers (RMSE Forec, in Table 1). The Figure 5 shows the prediction intervals obtained by the best-performing models in the training stage. In most

Table 1. Piezometer fitted models.

Piezometer	Model	RMSE Fit	RMSE Forec
PZ1	NNAR(1,1,2)[12]	0.287	0.398
	VAR(2) w/ mean	0.292	0.328
	ARIMA(1,1,0) w/ drift	0.295	0.554
	ETS(A,N,N)	0.296	0.303
	SNAÏVE	0.905	0.590
PZ2	NNAR(15,1,8)[12]	0.719	3.891
	VAR(5) w/ mean	1.652	1.143
	ARIMA(0,1,0)	1.744	1.831
	ETS(A,N,N)	1.744	4.128
	SNAÏVE	2.892	1.572
PZ3	NNAR(25,1,13)[12]	0.428	8.812
	ETS(A,N,A)	3.268	13.968
	ARIMA(1,0,1)(2,1,0)[12]	3.546	11.117
	VAR(5) w/ mean	4.076	12.277
	SNAÏVE	9.599	11.565
PZ4	NNAR(25,1,13)[12]	0.306	2.425
	ARIMA(1,0,1)(0,1,2)[12] w/ drift	1.550	2.646
	ETS(M,N,M)	1.707	4.335
	VAR(5) w/ mean	1.967	5.576
	SNAÏVE	3.547	2.253
PZ5	ARIMA(3,1,1)(2,0,0)[12] w/ drift	0.122	0.161
	VAR(2)	0.128	0.271
	NNAR(1,1,2)[12]	0.132	0.135
	ETS(M,Ad,N)	0.134	0.308
	SNAÏVE	0.494	0.399
PZ6	ARIMA(3,1,2) w/ drift	0.086	0.137
	VAR(5)	0.088	0.137
	ETS(A,Ad,A)	0.090	0.156
	NNAR(1,1,2)[12]	0.092	0.141
	SNAÏVE	0.288	0.186

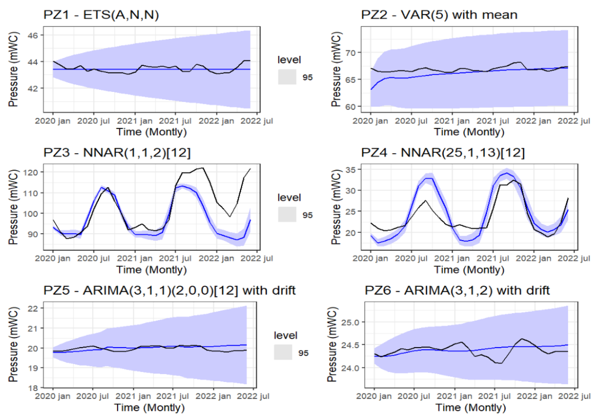

Figure 5. Uplift pressure forecasts by the most accurate models.

cases, the actual values were within the 95% confidence interval estimated for the predictions.

Therefore, among the models tested, the ones that were able to represent the past behavior best and predict the pressures measured by the piezometers were ETS(A,N,N) for instrument PZ1; VAR(5) for PZ2, NNAR(1,1,2)[12] for PZ3, NNAR(25,1,13)[12] for PZ4, ARIMA(3,1,1)(2,0,0)[12] for PZ5 and ARIMA(3,1,2) for PZ6. These results are similar to the research conducted by (Hua et al., 2023), in which ANNs models were used to obtain predictions for the uplift pressure time series at various points of a concrete dam, including the environmental components (upstream and downstream water levels, rainfall, temperature, and weather effects) among the predictor variables.

The uplift predictions generated by the models selected in this study will provide additional information to the engineers responsible for monitoring in the preventive evaluation of the dam's behavior, especially in the identification of anomalous behavior. In a complementary way, in the future, the models already selected can be used as a basis for obtaining limits (upper and lower) for the uplift, to provide more flexibility in detecting anomalies.

5. CONCLUSION

This study used an automated procedure to select and fit prediction models for the monthly mean pressure measured by six piezometers of the Itaipu Dam, which presented different characteristics (drifts, trends, seasonality). The simple exponential smoothing models could better predict the pressures of a piezometer that showed a decreasing trend and a drift. Vector autoregressive models resulted in lower errors in predicting the pressures of a piezometer with a slight trend and some outliers. The feed-forward neural network autoregression model had a better predictive performance for the piezometer series with seasonality and nonlinear characteristics. The autoregressive integrated moving average model produced more accurate predictions for the piezometer pressures with an increasing trend and stability in variance. The predictions generated by the models selected in this study can assist in the development of indicators of the behavior of the instrumentation and collaborate with the optimization of the time of analysis of the monitoring data of the pressures in the dam foundation.

For future research, suggest testing other prediction models considering uplift-related factors such as reservoir water level and ambient temperature.

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