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IV Hydraulic structures

PROGNOSIS ANALYSIS OF ARCH DAM BEHAVIOR BY HYBRID MODEL

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Abstract

The assessment of the structural stability and behavior of the dam during construction, at full reservoir and during the service period is of paramount importance for such structures. Each dam, in dependence of the type and dimensions, has installed system for technical monitoring that enables tracking of the dam behavior and assessment of the dam state throughout registration and interpretation of various data such as displacements, stresses, seepage etc.

The case study is double curvature concrete arch dam, with asymmetric shape due to the valley topography. In the paper are systemized acknowledgments for the comparison of the recorded data from technical monitoring of the dam and output results from spatial (3D) numerical model, created by application by application of SOFiSTiK code, based on Finite Element Method. In addition, a Neural Network model is created by recorded data from the technical monitoring. The both models create the so called hybrid model.

For both models are used input parameters such as variation of water level in the reservoir and air temperature, and the output results are compared with recorded values for water level in piezometers at specified nodes of the dam. The aim of the task is to compare and calibrate the output results from the both models and recorded values from the technical monitoring of the dam and to carry out prognosis modeling for the future behavior of the dam.

Keywords: arch dam, numerical model, FEM, SOFiSTiK, neural network, prognosis modelling.

1. Introduction

The dams, having in consideration their importance, dimensions, complexity of the problems that should be solved during the process of designing and construction along with the environmental impact are lined up in the most complex engineering structures (1) (2). The assessment of the structural stability and the behavior of the dam during construction, at full reservoir and during the service period is of paramount importance for such structures.

In this paper are systemized acknowledgments from the analysis of piezometer levels in the rock foundation of an concrete arch dam, obtained with application of numerical methods, based on Finite Element Method, with the code SOFiSTiK, as well as artificial neural networks model based on general regression neural networks. As follows, data on piezometer level obtained by both models for calibration and prediction piezometer levels in the rock foundation of an arch dam, located in France, will be commented. The aim of the task is to predict the dam behavior, that includes calibration (based on monitoring data) and prognosis stage (short-term and long-term) focusing on variable such as piezometer level.

2. Case study

The analysed dam is a double curve arch dam with asymmetric shape located in southern France (Fig. 1), constructed in the period between 1957–1960. The foundation of the dam is laminated metamorphic slate with high compressive strength, with present anisotropy in the left bank. The dam height above foundation is 45m, with crest width of 2m and width of the dam at the foundation of 6m (Fig. 2).

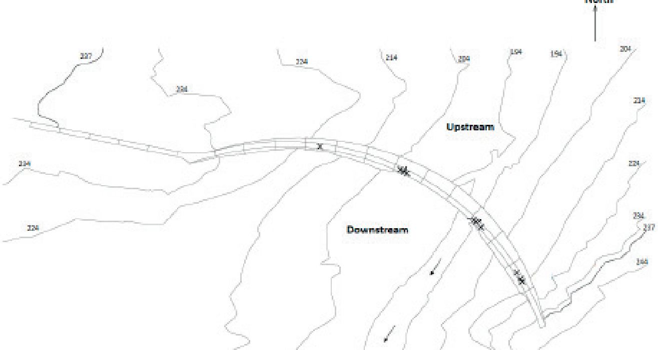

Figure 1. Layout of the case study dam

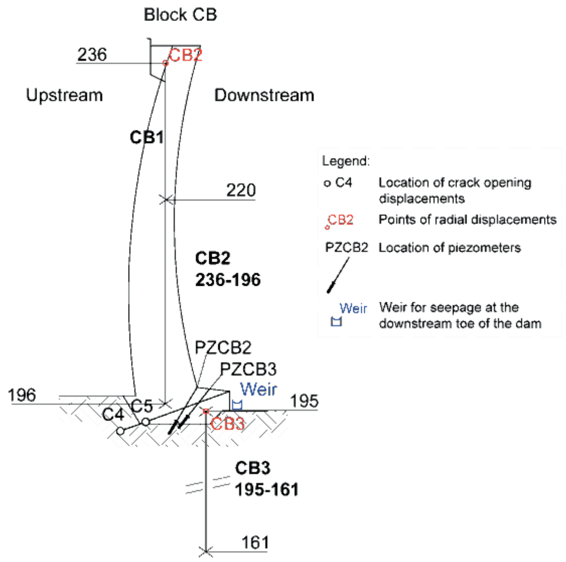

Figure 2. Central block section with display of monitoring instruments (right) (3) (4)

3. Numerical modelling by Finite Element Method

The numerical analysis of the dam is carried out with application of SOFiSTiK, a software delevoped in Munich, Germany. The software analyses are based on finite element method. It is a powerful numerical tool for analysis of specific phenomena, important for realistic simulation of dam's behavior, such as: discretization of the dam and foundation taking into account the irregular and complex geometry of the structure, simulation of stage construction, simulation of contact behavior by applying interface elements and etc. in order to assess the dam behavior and evaluate its stability.

The numerical experiment includes following steps: (1) choice of material properties and constitutive laws (concrete and rock); (2) discretization of the dam and the rock foundation and (3) simulation of the dam behavior for the typical loading states.

The linear material properties for the dam body (concrete) and the foundation (rock) are given in Tab.1.

Table 1. Material parameters.

Zone		dam body (concrete)	rock	Comment
γ_{spec}	kN/m^3	24.0	27.0	Unite weight
k_s	m/s		2.0e-05	Permeability coefficient
ν		0.350	0.450	Poisson coefficient
Alpha	1/C°	7.0E-06		Thermal expansion coefficient
E	GPa	22	3	Young's modulus of elasticity

Numerical analysis of piezometric levels at the foundation of the arch dam is carried out by plane (2D) model, where foundation with included grout curtain is modeled with plane elements. A powerful and reliable finite element should be applied in case where an analysis of structure with complex geometry and behavior is required, having in consideration that the correctly calculated deformations and stresses are of primary significance for assessment of the dam stability. In this case, for discretization of the dam body and the rock foundation is applied quadrilateral finite element, by 4 nodes. Namely, the model is composed of the rock foundation with included zone of grout curtain. The plane (2D) model has geometrical boundaries, limited to horizontal and vertical plane (Fig. 3), adopted according to the specified data. The discretization is conveyed by including zones of various hydraulic parameters in the model – rock foundation and grout curtain, approximately modelling the rock foundation per 75m upstream and downstream of the dam.

However, the hydraulic properties for the material in the rock foundation were not available. So, two-step calibration (in case of homogeneous and heterogeneous rock foundation) has been carried out for the value of the permeability coefficient k in accordance with the seepage values from the monitoring process. The estimated permeability coefficient for laminated metamorphic slate ranges in interval k=(10^{-7}÷10^{-9})m/s (5) (6). The permeability coefficient additionally is calibrated by the value of the full seepage flow directly below the dam, specified as measured values in weir at gallery located at the downstream toe of the dam. So, according to the available measuring data for water level at

232.0 m the average registered seepage flow is 8 l/min. From the registered reservoir water levels and seepage flow it can be noticed general correlation, however in some periods there is discrepancy in the measured values that could be indication that the seepage flow is caused by additional influences then the seepage process in the rock foundation. The seepage analysis was carried out for H=232.0 m as upstream boundary condition and H=0 m as downstream boundary condition, by applying Darcy flow rule adopting the rock foundation as heterogeneous flow medium, composed of rock material (laminated metamorphic slate) and two sections (vertical and inclined) of grout curtain, by assumed permeability coefficient in first iteration $k_r=1\times10^{-7}$ m/s for the rock zone. By the first-step (initial) calibration calculation of the permeability coefficient for homogeneous rock foundation was obtained value of $k=2.89\times10^{-8}$ m/s, applied in the calculation for the full calibration and prognosis analysis of the piezometric levels and seepage. Due to the grout curtain in the rock foundation (heterogeneous zone), additional calibration were carried out, in order to match the measured seepage flow Qm=8 l/min and thus obtaining value of permeability coefficient for the rock foundation $k_{rf}=12.5\times10^{-8}$ m/s and permeability coefficient for the grout curtain $k_{gc}=2.5\times10^{-8}$ m/s, used as input parameters for the seepage calibration and prognosis stage, for the FEM model (Fig. 3).

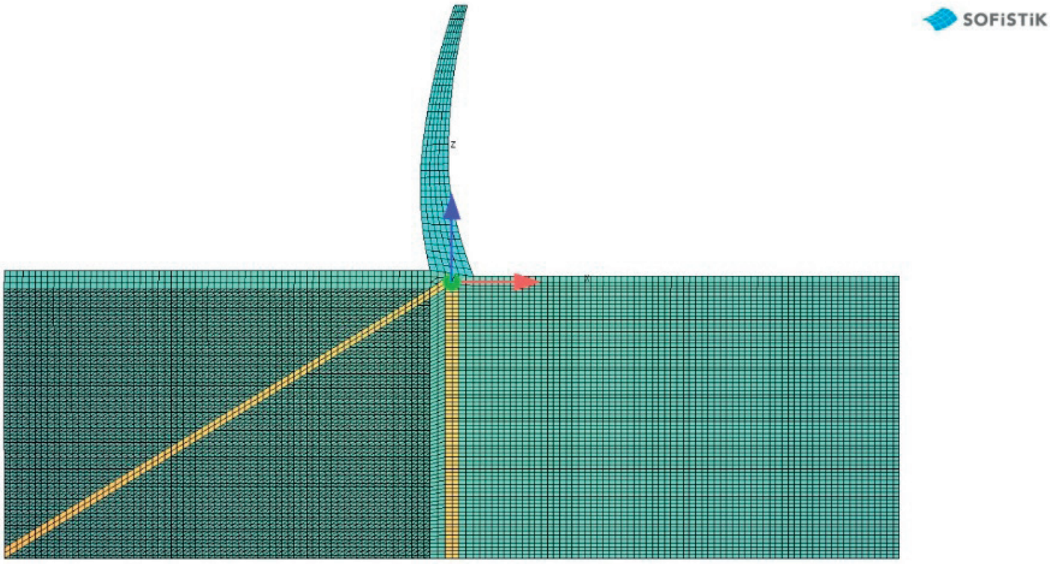

Figure 3. View of the plane numerical model, material distribution and FEM, discretized with total of 15511 elements and 11252 nodes

4. Neural networks modelling

Artificial neural networks are typical example of a advanced interdisciplinary tool that helps solving various different engineering problems which could not be solved by the clasical modelling and statistical methods (7). Neural networks are capable of collecting, memorizing, analyzing and processing large number of data gained from some experiments or numerical analyses. They are an illustration of sophisticated modelling technique that can be used for solving many complex problems. The trained neural network serves as an analytical tool for qualified prognoses of the results, for any input data which were not included in the learning process of the network. Their operation is reasonably simple and easy, yet correct and precise. The artificial neural networks, together with the fuzzy logic and genetic algorithms, belong to the group of symbolic methods of intelligent calculations and data processing that operate according to the principles of soft computing. Neural networks are developed as a result of the positive features of a few different research directions: data processing, neuro-biology and physics (7). Researches around the world showed that neural networks have an excellent success in prediction of data series and that is why they can be used for creating prognostic models that could solve different problems and tasks (7; 8). For practical application of artificial neural networks, it is not necessary to use complex neuron models. Therefore, the developed models for artificial neurons only remind us to the structure of the biological ones and they have no pretension to copy their real condition (9). The artificial neuron receives the input signals and generates the output signals. Every data from the surrounding or an output from other neurons can be used as an input signal.

ANN neural networks functioning is analog to the way human neuron networks function. The neuron in the human body is consisted of axon, soma and dendrite. The soma is the body, dendrites are connections to other neurons and axon transfer electric signals among cells. ANN is also consisted of neurons, and they practically imitate biological processes that normally happen in the neuron network of a living organism. The mathematical model of artificial neural networks is basically a network comprised of a large amount of neurons interconnected with connection links of specifically defined weight coefficients. ANN consists of: (1) input data layer, (2) weight coefficients, (3) hidden layer/s and

(4) output data layer. Weight coefficients are key elements in neural netowkrs. Their value represents the relative importance of each neural input and they define the ability of input activation of neurons. Neural networks have the ability of 'training/learning'. This process occurs as a result of adjustments in the value of weight coefficients, based on the array of input and output data. Activation function defines the output of a neuron given an input or set of inputs. Linear or non – linear functions serve as activation functions, however, one of the most commonly used one is sigmoid function:

$$Y_t = \frac{a}{1+e^{-y}}$$

As follows, by applying Generalized Regression Neural Network (GRNN) specifically NeuralTools software from Palisade corporation, data prediction in case of arch dam are shown. The data set used for training is basically values of the given measured data. In the training process, 70% of the data is used for training and 30% is used for validation. The variables are classified as independent or dependent, depending on their role in the prediction process. The dependent variable is the variable to be predicted. The independent variables are the "explanatory" variables used to predict the dependent variable. Cases where the dependent variable values are known are used to train and test a neural network.

The modeling by application of GRNN is based on the following variables: (1) water level in piezometer PZCB2 as dependent numeric value and water level in the reservoir as independent numeric value, and (2) water level in piezometer PZCB3 as dependent numeric value and water level in the reservoir as independent numeric value.

5. Calibration process

The calibration process is carried out by comparison of the measured and calculated piezometer levels for a time series of 12 years (2000–2012), for both the FEM and neural networks (NN) model.

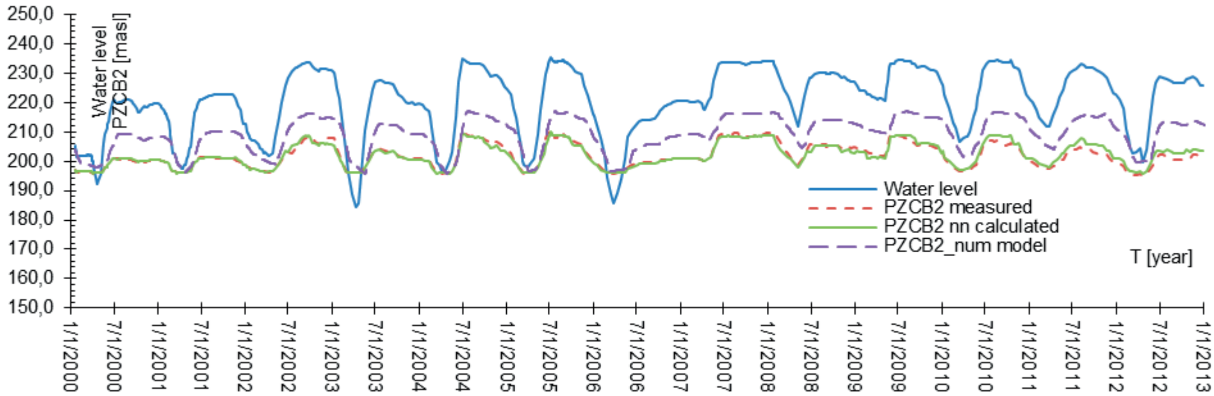

Figure 4. Display of measured and calculated time series of piezometer levels in piezometer PZCB2 for 2000–2012

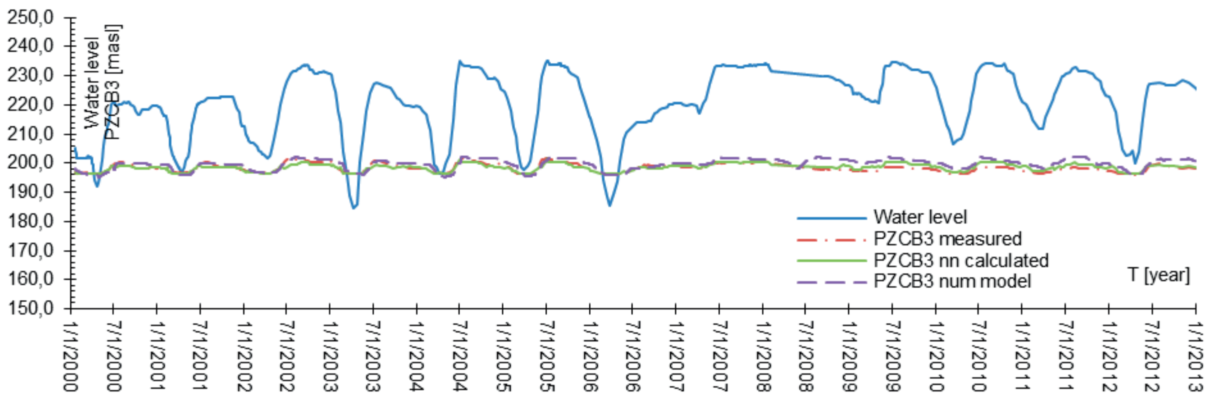

Figure 5. Display of measured and calculated time series of piezometer levels in piezometer PZCB3 for 2000–2012

In Fig. 4 and Fig. 5 graphs are shown from output results of the calibration process for measurements in piezometers PZCB2 and PZCB3, for a time series of 12 years of measured data. The calibration process modelling is done by both FEM and neural networks (NN) model.

By comparison of the piezometric levels for piezometers PZCB2 and PZCB3, calculated by NN model (Fig. 4 and Fig. 5) it can be noticed excellent matching of the measured and calculated data regarding the distribution and the values and some lees good mathcing by the FEM model. The calculated piezometric levels by NN model, in analogy of the calculated values from the FEM model for seepage analysis, are in full correlation with the reservoir water level.

The timeline of 12 years in the calibration process is used as data for training the neural networks. The trained neural networks are afterwards used for prediction of the behavior of the water level in the piezometers for short and long term.

As follows, accuracy generated parameters for the NN models are given for both piezometer PZCB2 (Table 2) and piezometer PZCB3 (Table 3).

Table 2. Accuracy parameters for the neural networks model for PZCB2, for both the training and testing period

Parameter	Training	Testing
Root Mean Square Error	0.8597	1.072
Mean Absolute Error	0.5619	0.7393
Std. Deviation of Abs. Error	0.6507	0.7761

Table 3. Accuracy parameters for the neural networks model for PZCB3, for both the training and testing period

Parameter	Training	Testing
Root Mean Square Error	0.7792	0.7581
Mean Absolute Error	0.5574	0.5484
Std. Deviation of Abs. Error	0.5445	0.5234

6. Prognosis process

The prognosis stage consists of short-term and long-term prediction of the specified variables. Namely, the short-term prediction includes period January, 2013-June, 2013, while the long-term prediction captures period July, 2013-December, 2017. The prediction analyses are conducted for both the numerical and neural networks model, for piezometer levels in PZCB2 and PZCB3.

The calculated piezometric levels for piezometers PZCB2 and PZCB3 for the short-term and long term prognosis, as expected, are varying in correlation with the water level in the reservoir (Fig. 6 and Fig. 7) apropos are in acordance with the hydraulic loading.

The maximal and minimal calculated values for the piezometer levels in PZCB2 are varying between 205.5 masl and 195.5 masl, whereas piezometer levels in PZCB3 are varying in a tight range approximately to 200.0 masl.

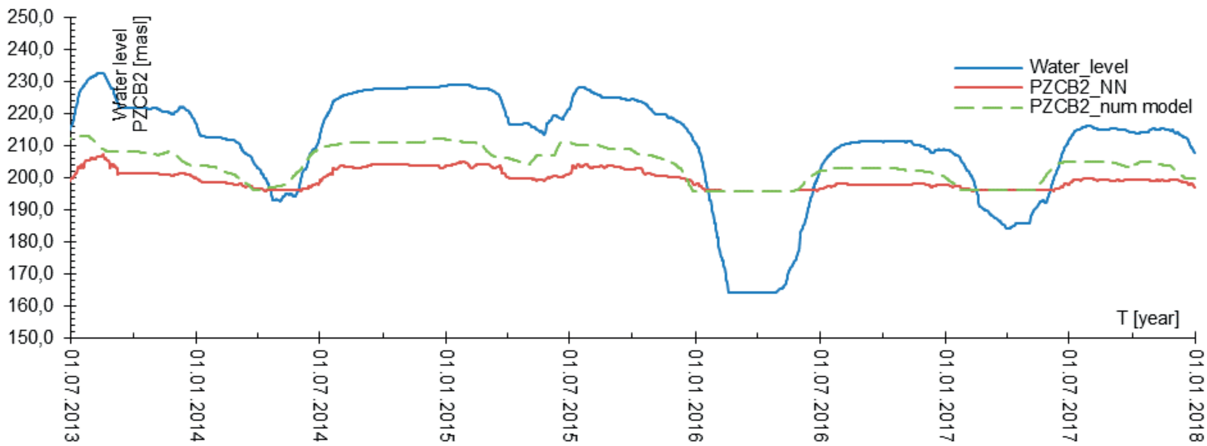

Figure 6. Prognosis calculated time series of piezometer levels for PZCB2 for 2013-2017 by NN and numerical model

Using the accuracy parameters from the calibration period derived from the neural networks model, a warning level corridor of permissable variation of piezometer levels is defined. This corridor represents boundaries of safe variation of the piezometer water level. The corridor is defined with added value (3·Standard Deviation of Abs. Error) to the predicted values for piezometer level. Such levels are defined in order to establish coridors for the permisible piezometric levels for piezometer PZCB2 and PZCB3, that are not to be exceeded by the monitoring values for the future period. Any excidance of the specified coridor values would indicate to iregular occurence in the dam foundation behaviour, that will need to be investugated additionaly.

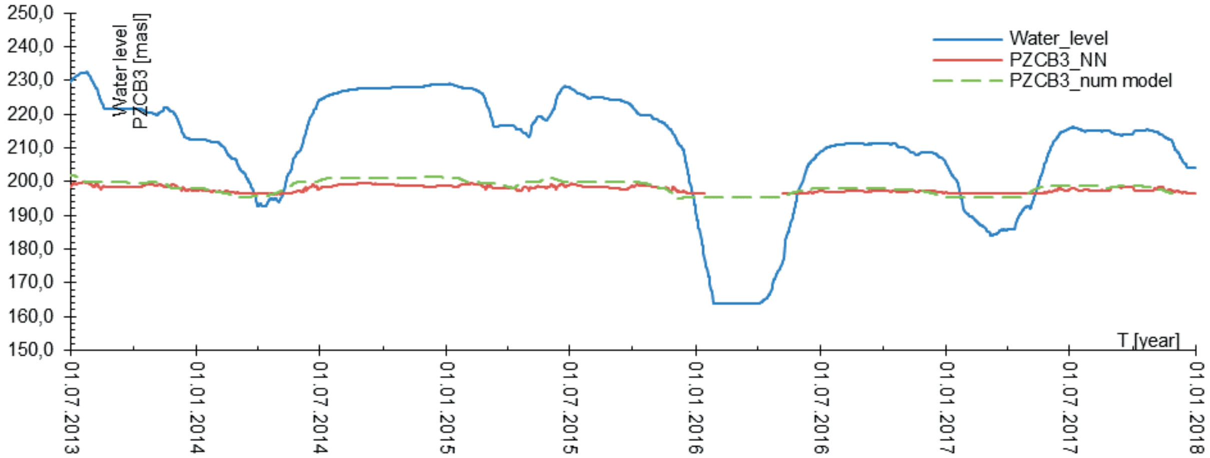

Figure 7. Prognosis calculated time series of piezometer levels for PZCB3 for 2013-2017 by NN and numerical model

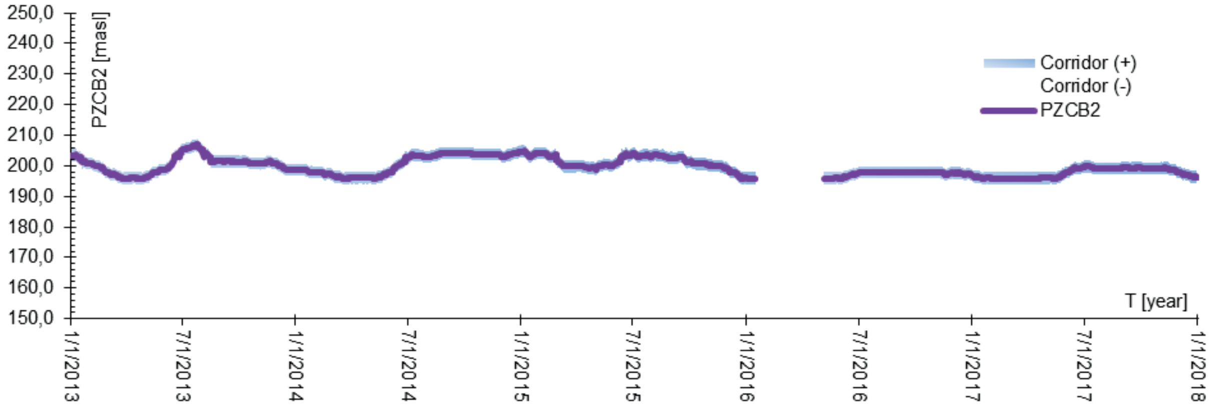

Figure 8. Warning level corridor of perimsable variations for piezometer level in PZCB2

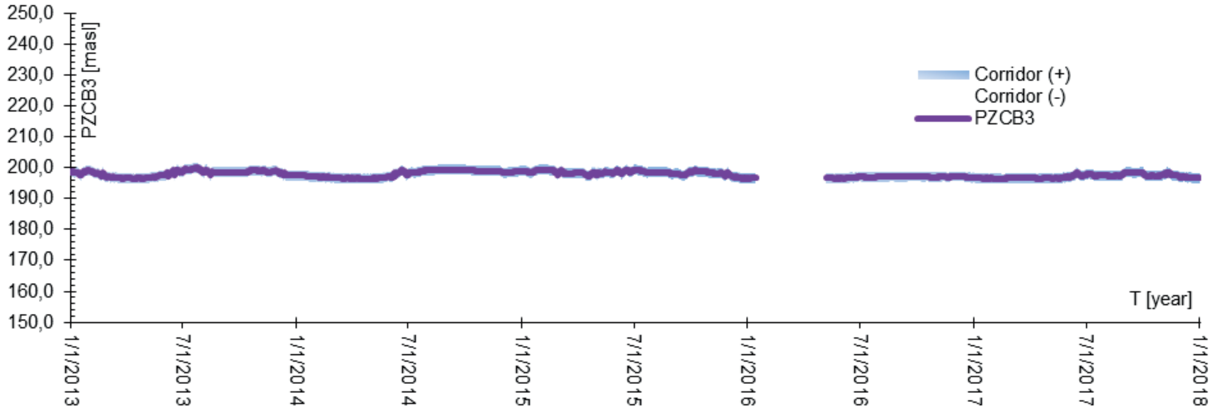

Figure 9. Warning level corridor of perimsable variations for piezometer level in PZCB3

7. Conclusions

The piezometer level at the foundation of the dam during the service period for variation of the water levels in the reservoir was simulated by application of the Finite Element Method with plane (2D) numerical model and Neural Networks model.

The numerical analysis was carried out by taking in consideration the specified data for the numerical model and variations of the reservoir water level.

The prediction of the piezometer levels was analyzed in two stages – calibration and prognosis stage. From the carried out numerical experiment of simulation for analysis and prediction of the piezometer levels, following conclusions are derived:

1. For the calibration stage in the FEM numerical model, by comparison of the calculated and measured piezometric levels for piezometers PZCB2 and PZCB3 good matching of the records is obtained regarding the distribution and less good matching regarding the values.

2. For the calibration stage in case of NN model, by comparison of the calculated and measured piezometric levels for piezometers PZCB2 and PZCB3 excellent matching of the records is obtained regarding both the distribution and the values.
3. For the prediction stage, by comparison of the calculated values for piezometric levels from the FEM model and neural networks model, piezometric levels for piezometer PZCB2 shows good matching of the records regarding the distribution and less good regarding the values.
4. For the prediction stage, by comparison of the calculated levels from the FEM model and neural networks model, piezometric levels for piezometer PZCB3 shows very good matching of the records regarding both the distribution and the values.
5. The overall calcualted piezometer levels in the piezometers PZCB2 and PZCB3 in the arch dam foundation, taking in consideration the findings from the calibration and the prognosis stage, are within the expected mode for such structure and applied hydraulic loading.
6. According to the measured and calculated values for the variables by NN model, warning levels corridors are established by applying criteria of $3\times\sigma$, where σ is standard deviation of absolute error, generated by the NeuralTools code, that would indicate of iregular occurence in the dam foudnation in case of their excidance.
7. General conclusion can be drawn out for the analysis task that Neural Network model provided improved comparation and matching of the calculated vs measured data for both variables compared with the FEM model.

References:

[1] Tanchev, Ljubomir. Dams and appurtenant structures, 2nd edition. London, UK: A.A. Balkema Publ., CRC press, Taylor&Francis Group plc, 2014.

[2] P. Novak, A.I.B. Moffat, C. Nalluri. Hydraulic structures, 3rd edition. London, UK: Taylor&Francis Group, 2007.

[3] Calibration analysis of seepage flow at arch dam foundation – a case study. Stevcho Mitovski, Ljupcho Petkovski, Frosina Panovska. Ohrid: Macedonian Association, 2022. 5th Symposium of the Macedonian Association for Geotechnics.

[4] Behavior prediction of a concrete arch dam. Stevcho Mitovski, Gjorgji Kokalanov, Ljupcho Petkovski, Frosina Panovska. 2022. ICOLD Benchmark Workshop 2022.

[5] Lianyang, Zhang. Engineering properties of rocks. Elsevier Ge-Engineering Book Series. 2016, Vol. 4.

[6] Robbin Fell, Patric McGregor, David Stapledon, Graeme Bell, Mark Foster. Geotechnical engineering of dams. London, UK: Taylor&Francis Group, 2015.

[7] Neural networks in civil engineering II: Systems and application. I. Flood, K. Nabil. 1994. Computing in Civil Engineering.

[8] Modeling construction processes using artificial neural networks. I. Flood, C. Paul. 4, 1996, Automation in Construction, Vol. 4, pp. 307–320.

[9] Simulating the construction process using neural networks. Flood, I. Bristol: s.n., 1990. Proceedings of the 7th ISARC – International association for Automation and Robotics in Construction.

[10] Lazarevska, Marijana. Modeling of management of construction projects wih implementation of fuzzy neural networks. Podgorica: Univerzitet Crne Gore, Gradzevinski fakultet, 2014.

[11] Adeli, H. Neural networks in civil engineering: 1989–2000. Computer-aided civil and infrastructure engineering 16, no. 2. 2002, pp. 126–142.