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Prognostic model of radial displacements of concrete arch dams

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Professional paper

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Prognostic model of radial displacements of concrete arch dams

This paper presents a prognostic model for the radial displacement of a concrete arch dam based on long-term monitoring data. The model is developed using artificial neural networks (ANNs), with reservoir water level, air temperature, and groundwater level employed as input variables. The dataset covers 48 years of operational monitoring of the Piva Dam. The model was implemented in the Python environment using the TensorFlow and Keras libraries. Model performance was evaluated using the Mean Absolute Percentage Error (MAPE). The optimal model (ANN 23) achieved a MAPE of 8.34% for the training dataset and 7.73% for the testing dataset. The results demonstrate that the proposed model provides reliable predictions of the structural behaviour of the dam and represents an effective tool for supporting dam monitoring systems.

Key words:

monitoring, radial displacement, artificial neural networks, prognostic model, concrete arch dams, dam monitoring, machine learning

Stručni rad

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Prognostički model radijalnih pomicanja betonskih lučnih brana

U radu je razvijen prognostički model radijalnoga pomicanja betonske lučne brane na osnovi dugoročnih mjernih podataka. Model je utemeljen na umjetnim neuralnim mrežama, pri čemu su kao ulazne varijable upotrijebljeni kota akumulacije, temperatura i razina podzemnih voda. Podaci obuhvaćaju razdoblje od 48 godina eksploatacije brane "Piva". Model je implementiran u Python okruženju primjenom biblioteka TensorFlow i Keras. Točnost modela ocijenjena je s pomoću srednje apsolutne postotne pogreške (MAPE), pri čemu optimalni model (NMC 23) ostvaruje pogrešku od 8,34 % za skupu za učenje i 7,73 % za testni skup. Rezultati pokazuju da razvijeni model omogućava pouzdanu procjenu ponašanja konstrukcije te da je učinkovit alat za podršku sustavima monitoringa brana.

Ključne riječi:

oskultacije, radijalni pomak, neuralne mreže, prognostički model, betonske brane, monitoring brana, strojno učenje

1. Introduction

The concrete arch dam "Piva" is an asymmetric concrete arch dam with double curvature. With a structural height of 220 m, it ranks among the world's highest dams and is recognised internationally. The impoundment of the Piva River formed a reservoir (Lake Piva), whose water is used for peak-load electricity generation at the "Piva" hydropower plant. The "Piva" concrete arch dam represents one of the most significant hydraulic engineering structures in the region. Completed in 1976 after ten years of construction, the dam entered operation with an initial impoundment of the reservoir. The reservoir has a storage capacity of 824.5 × 10^6 m^3 and surface area of 15.4 km^2 at the normal water level elevation of 675 m above sea level. Owing to its asymmetric arch shape, variable thickness, and complex geometry, the dam exhibits a highly nonlinear structural response to external loading. Such structures require continuous monitoring and the development of reliable predictive models to assess their structural behaviours.

The thickness of the dam varies from the base (where it is the greatest) to the crest (where it is the smallest). In addition to the variable thickness, the arch curvature is asymmetric. The intrados and extrados of the arch are circular arcs, whereas the arch axis (centreline) is an ellipse formed by combining the circular segments generated from three centres. The intersections of these circular segments create an asymmetric arch geometry. The left abutment of the canyon is steeper than the right, and deformation moduli of the surrounding rock mass are nonuniform. Consequently, the upper-right abutment is supported by a system of horizontal rock anchors that transfer loads to higher-quality rock with geotechnical properties comparable to those of the left abutment. The dam foundation joints can be approximated using parabolic curves. This configuration provides an optimal fit for the dam within the canyon profile while accounting for the orientation of tectonic discontinuities, which play an important role in the overall stability of the structure. Figure 1 shows the developed dam profile with vertical cantilevers (18 in total) and horizontal galleries (five in total).

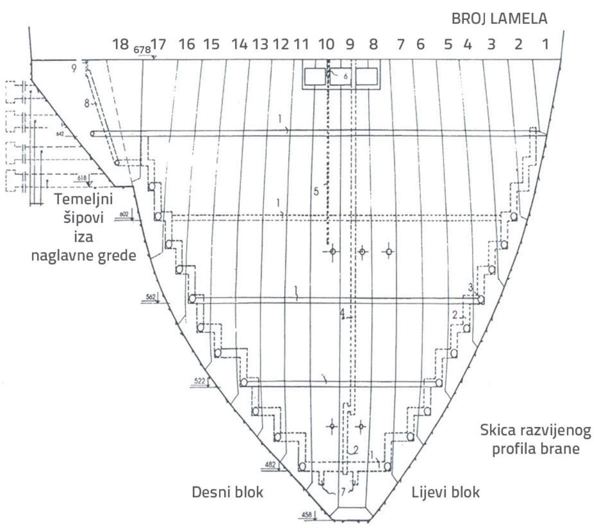

Figure 1. Developed profile of the dam

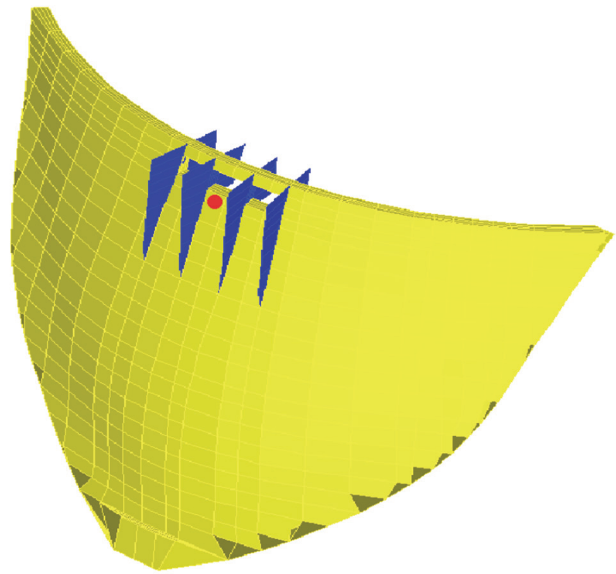

Figure 2. Linear numerical model of the dam (SAP2000)

Figure 2 shows the characteristic measurement points used as input data for training the neural network and the point located in the central cantilever (red point) at which the radial displacement is predicted.

The central part of the dam crest contains three spillway bays that are activated during periods of excessive reservoir inflow. Each spillway bay measures 13 m × 5 m and is located at an elevation of 670 m above sea level. The dam consists of 18 cantilevers and five inspection galleries situated at 642, 602, 562, 522, and 482 m above sea level.

When analysing the behaviour of structures of this type, various loading actions (hydraulic, gravitational, and seismic) produce a range of structural responses. A satisfactory structural response is considered to be one that remains within the elastic range (linear state). In contrast, an unsatisfactory response, in which the structure sustains certain damage without collapsing, is referred to as plasticity (nonlinear state). The structural response largely depends on the interaction between the structure, reservoir, and foundation (*fluid–structure interaction*, FSI), whereby different modelling approaches can lead to significant differences in predicted displacements and stresses [14].

The "Piva" concrete arch dam consists of 18 mutually independent cantilevers. The space between the cantilevers is filled with high-grade concrete (joint fill) to prevent water leakage caused by the hydrostatic pressure exerted by the reservoir. Connections are provided precisely at these locations (joints) to allow the redistribution of the stress arising from various actions on the dam.

Previous research on concrete arch dams has made valuable contributions. However, considering the importance of the subject, further investigation is required. Several authors have analysed the structural response of dams to external loading using theoretical approaches based on three-dimensional (3D) numerical models developed using commercial software packages, whereas other studies have relied on measured data.

The dynamic behaviour of concrete dams is largely governed by their inherent dynamic characteristics, which are described by their natural frequencies and mode shapes. These parameters provide the basis for the structural response analysis. In engineering practice, it is often sufficient to consider a limited number of dominant vibration modes because they have the greatest influence on the global behaviour of the system [15].
A safety assessment had been conducted in the Norwegian city of Norvik to evaluate the dam under design loading conditions. The buttresses satisfied the required load-bearing capacity; however, most buttresses did not satisfy the required sliding safety factor. Nevertheless, the dam exhibited only minor signs of damage, with slight cracks visible at certain locations. For this reason, sensors were installed at critical locations, and long-term monitoring data are used to support future dam management decisions [1]. In addition to experimental measurements and artificial intelligence methods, numerical modelling based on actual hydrological and geometric data plays a significant role in the behaviour of hydraulic structures. The application of 3D models enables the analysis of complex processes and verification of the consistency between measured and calculated values, thereby improving the understanding of system behaviour and validating the results obtained by other methods [13].
Contemporary approaches to dam monitoring increasingly incorporate advanced data processing methods and artificial intelligence. The application of 3D testing methods in combination with neural network models enables continuous monitoring of structural conditions and identification of potential damage based on measurement data. This approach indicates that the integration of measurement data with intelligent models is an effective tool for the analysis and prediction of the hydraulic structure behaviour [16].
A study presented at the 19th Symposium of Civil Engineers held in North Macedonia investigated the application of a coupled thermomechanical analysis of a dam under static loading conditions. A 3D numerical model was developed using the finite element method. Three different behavioural scenarios were simulated depending on the static loading conditions (reservoir water level and temperature): high water level and low temperature (resulting in a downstream radial displacement of 25.4 mm), low water level and high temperature (resulting in an upstream radial displacement of 26.6 mm), and high water level and high temperature (resulting in a displacement of 19.3 mm towards the right bank at 20 % of the crest length in the upstream direction) [2]. The displacement values of concrete dams were relatively small and typically ranged from a few millimetres to several centimetres, indicating a high stiffness of the structure and predominantly elastic behaviour under the operating conditions.
The literature also includes a study on the assessment of the dynamic behaviour of the Ermenek Dam, the second-highest dam in Türkiye. This study was conducted based on geodetic measurements and the finite element model analysis during the initial reservoir-filling period. Eight periods of measured deformation were considered, up to the point at which the reservoir reached full capacity. The responses of the dam to different reservoir water levels and temperature variations were investigated in detail. The total displacements at the centre of the dam exhibited periodic and linear deformation trends corresponding to the temperature changes and hydrostatic pressure, respectively. Moreover, the deformations obtained via the finite element method and geodetic observation correlate with one another [3].
Structural "health" monitoring and prediction play a key role in the life cycle of infrastructure systems such as dams. Such a process facilitates better-informed decision-making regarding maintenance planning and life-cycle management. A group of authors from Concordia University became interested in a case study of a dam experiencing slow, irreversible upstream movement in its central section. The primary objective of this study was to confirm and establish a level of confidence in numerical modelling by comparing the displacements recorded by seismic, hydrometeorological, geotechnical, and geodetic instruments. To obtain the results, a thermomechanical analysis was performed on a 3D model of the dam-foundation-reservoir system. In addition, the study employed the well-known statistical model", Hydrostatic Season Time" (HST), based on multivariate regression analysis for predicting future dam displacement using relevant data from sensors installed on the dam. The results obtained indicated a good correlation between the observed dam displacement based on instrumentation data and that calculated using the finite element analysis, considering the presence of vertical joints between the dam cantilevers. Moreover, the "HST" model closely matched the data measured using the instruments and, as such, demonstrated good predictive capability for the future behaviour of the dam, as well as for isolating the effects of different parameters on dam displacement [4].
The application of various prediction methods provides a more effective approach to manage the operation of concrete dams. In the twenty-first century, the leading approach to prediction, which guarantees high accuracy, is artificial intelligence; in particular, hybrid models based on neural networks have demonstrated high accuracy in modelling dam deformations [10]. Professors from the University of Montenegro addressed the application of artificial intelligence to estimate the costs of integral bridges. Among the developed models, the optimal artificial neural network model achieved high prediction accuracy with a mean absolute percentage error (MAPE) of 13.4 % [5].

2. Materials and methods

Numerous electrical and mechanical instruments were installed to monitor displacements within the dam body. Because these instruments have been in operation since the beginning of the service life of the dam and are located in demanding environmental conditions characterised by high humidity in both grout and longitudinal galleries, many electrical instruments are no longer functional, whereas mechanical instruments remain fully operational.

The following mechanical instruments were used:
- Plumb lines (used to measure radial and tangential displacements in cantilevers 5, 9, and 14)
- Joint meters (used to measure radial displacements at joints between cantilevers)
- Extension meters (used to measure the deformability of rock masses at dam abutments)
- Clinometers (used to measure the angle of rotation of the dam body at vertical joint).

This study focused on measurements obtained from the plumb line installed in the central cantilever of the dam (Cantilever No. 9). This cantilever was selected because the largest displacements occurred at this part of the dam, particularly at the dam crest.
Figure 2 shows the linear numerical model developed using the SAP2000 software package, which was used as a reference framework for assessing the global behaviour of the dam and for comparison with the results obtained from the measurement data [15]. The model was developed using surface (shell) elements because the focus of this study was on the global deformation and overall structural response of the dam, rather than on the detailed stress distribution throughout the dam body, implying that the use of solid elements was not necessary in this case. Linear analysis assumes a proportional relationship between the external load and structural response, which represents an acceptable simplification under operating conditions and enables a reliable assessment of the dominant parameters governing the behaviour of the dam [14]. In the numerical analysis of complex structures such as dams, solving problems with a large number of degrees of freedom requires certain simplifications, whereby the dominant response modes that have the greatest influence on the overall behaviour of the system are typically isolated, whereas other effects are considered to have less significance [15].
This approach makes it possible to obtain the values of the internal forces along the boundary lines of the elements. The values obtained coincided with those measured by the mechanical instruments within the dam. The red point shown in the central cantilever in Figure 2 represents the location at which the displacement prediction was obtained using a neural network built into the *Python* software package into which the previously measured data were entered.

Figure 3. Joint meter located at the dam crest (cantilever 9) where the measurements used for the neural network were obtained

The neural network was trained on various input variables implemented in *Python* code. The adopted approach is consistent with the standard application of multilayer perceptron (MLP) models to structural deformation regression problems. Table 1 lists the input parameters and their minimum, maximum, and mean values.
Therefore, the data used to develop the mathematical model must be comparable. The data used in this study represent the actual measurement data collected during the long-term monitoring of the dam. This approach enables the linking of numerical and empirical models, whereby validation is performed based on real measurements and their mutual relationships, in accordance with contemporary methodologies in hydraulic engineering [13]. A similar approach has been applied in contemporary research, where combining measurement systems with advanced data analysis methods enables a more reliable assessment of structural conditions. The integration of real measurement data and artificial neural network models improves the prediction accuracy and provides a better understanding of system behaviour [16]. Given that the values were obtained from a database spanning the period from the first years of the operation of the dam to the present, representing a time span of 48 years, a check was performed, and it was established that the values consistently followed one another. However, care must be taken to ensure that the compared data points match the corresponding data points for the symmetric time of year.
According to the dam-monitoring program (from whose archive the database used to develop the model was obtained), the following physical and telemetry measurements were performed.

Table 1. Input parameters with boundary values

Input variable No.	Description of the input variable	Data type	Unit	Min	Max	Mean value
Input 1	KA	Numerical	**m n.m.**	641.8	674.76	662.3
Input 2	T	Numerical	**°C**	-12.84	28.14	6.9
Input 3	P	Numerical	**cm**	41.1	162.25	85.46
The input parameters have different units of measurement. which further emphasises the need for scaling before model training. RWL – Reservoir water level (m.a.s.l.) T – Concrete temperature (°C) P – Piezometer readings (groundwater level. left and right bank. cm)						

- Dam displacements using plumb lines
- Rotation of selected points on the dam
- Joint openings between dam cantilever blocks
- Foundation-rock deformations
- Reservoir water level
- Concrete temperature
- Air temperature
- Water temperature
- Local concrete deformations
- Groundwater level
- Contact pressure at dam–foundation interface
- Uplift pressure acting on dam foundation
- Pore water pressure in concrete
- Relative horizontal displacements of points at the dam crest in Cantilevers 5, 9, and 14 along the principal radial direction alignment [6].

Of all the measurements listed above that are performed during regular auscultation (dam monitoring), the following three (reservoir water level, temperature, and groundwater level) are the most significant, as their variations are, to the greatest extent, responsible for the opening or closing of the dilatation joint in the central cantilever at the dam crest. Therefore, these measured values were used to predict displacement using the neural network. Only measured data on radial displacement were used to train the neural network, whereas the SAP2000 numerical model was not used to generate data, but rather served as an auxiliary tool for interpreting the global behaviour of the structure. The effects of concrete creep, concrete shrinkage, and residual stresses arising from the cement hydration process were not explicitly modelled in this study. However, given that the long-term measurement data spanned a period of 48 years, these effects were implicitly contained within the measured values and were thereby indirectly incorporated into the model training process. In this way, their cumulative influence on the deformation behaviour of the structure was accounted for through historical data, enabling a more realistic approximation of the actual behaviour of the dam [14].

The reservoir water-level represents the height of the water column in the reservoir, measured in meters. The reservoir water-level values contained in the database were recorded daily, four times a day (every 6 h), from the beginning of the operation of the dam, that is, from the initial reservoir impoundment. Measurements were performed using a staff gauge anchored to the face of the dam (upstream). Under poor weather conditions (fog or snow) or when the reservoir water level was too low to allow visual reading from the dam crest, measurements were taken using a Rittmeyer water level gauge. The operating principle of a Rittmeyer gauge is based on an electrical probe equipped with a float. Changes in the water level were detected according to the principle of communicating vessels, and the resulting signal was processed by a "data logger" before being transmitted electronically to a computer for display and recording. Annually, the highest reservoir water levels generally occurred during spring and autumn, whereas the lowest levels were typically recorded during summer.

The temperature distribution within a structure is highly complex because it depends on numerous factors, the most important of which are the air temperature, water temperature, rock temperature, season, solar radiation, geometric characteristics of the structure, and properties of the materials used in its construction. The temperature data used as the input variables consisted of concrete temperature measurements obtained at a specific location and recorded daily. The temperature of the concrete mass was measured using electrical probes embedded in the concrete and positioned 70 cm from the concrete–water interface towards the interior of the dam body. The output signal from the temperature sensors was expressed in hertz (Hz) and converted into degrees Celsius (°C) using a predefined conversion formula. Thermal analysis of the temperature distribution within the dam body was not performed as part of this study because the research focused on the development of a predictive model based on measured data. The effect of temperature was incorporated through actual measurements of the temperature field within the structure, thereby accounting for its influence indirectly during the training of the artificial neural network. Given that the objective of this study was to predict dam displacements based on real monitoring data, additional numerical thermal analyses were not considered essential.

The groundwater level was measured in circular boreholes using a water level meter. The boreholes are located in the galleries (grout curtain galleries), which extend perpendicular to the curvature of the dam arch, and are positioned on both the left and right abutments, extending approximately 700 m into the rock mass. The water-level meter consists of a reel around which a cable is wound, with a length of up to 200 m, and a sensor that sends a signal at the moment of contact with the water at its tip. Groundwater directly influences the deformability of the foundation rock at dam abutments. The occurrence of liquefaction in these zones may lead to a loss of foundation stability, resulting in stress redistribution within the dam body, and consequently, the development of cracks.

As the input parameters of the model have been defined, the

Table 2. Output variable with boundary values

Output variable No.	Description of the output variable	Data type	Unit	Min	Max	Mean value
Output 1	RA	Numerički	cm	4.39	6.736	5.65
RA - Radial displacement						

output parameters must also be specified. Based on the present study, a single output parameter, namely radial displacement, was established. The output variable, together with its boundary (minimum and maximum) and mean values, is presented in Table 2 [7, 8]. The model development procedure was conducted systematically and consisted of a defined number of steps, with identical conditions ensured for each model.

3. Results

After defining the output variable, which represents the objective of the model, the input variables are determined. Their selection requires careful consideration of their influence on the output variable. Above all, the input variables determine what the neural network learns and how well it generalises to new data; that is, how it forms the foundation of the entire modelling process. Proper selection, scaling, and preprocessing are as important as the design of the neural network itself.

The next stage in the model development process is data preprocessing, in which all variables are transformed into a common range of values. High-quality data are obtained by scaling. The scaling ranges of the input and output variables depend on the activation function used in the output layer. Data scaling can also be performed through standardisation and normalisation. The purpose of these procedures is to transform the data into a comparable scale. In this study, scaling was applied to the entire dataset of the measured values using the StandardScaler and MinMaxScaler methods. The dataset used in this study comprised continuous daily measurements over a 48-year period. Prior to model training, the input and output variables were standardised and normalised using the StandardScaler and MinMaxScaler methods. Scaling was performed on the complete dataset to ensure stability and efficiency of the neural network training process.

After the data preparation stage was completed, the dataset was divided into two subsets: training and test sets. The training set was used to train the neural network, and the test set was used to evaluate its performance. When selecting the test dataset, it is important to ensure that the data is suitable for solving the problems under consideration. Previously, several authors have provided recommendations that generally agree on data splitting ratios of 90 % to 10 %, 80 % to 20 %, 85 % to 15 %, or 70 % to 30 % [9]. However, if the characteristics of the model require different distributions between the training and test datasets, other data-partitioning strategies may be adopted. In this study, the training and test datasets were divided into three ratios: 80–20 %, 90–10 %, and 85–15 % [10, 11]. The model was calibrated using the training dataset and its performance was validated on a separate test dataset that was not used during the training process, thereby ensuring an objective assessment of the generalisation capability of the model. The data were randomly partitioned to avoid bias during model training.

All the predictive models used in this study were developed in the *Python* programming environment. The model was implemented using the *Python* programming language by applying the *TensorFlow* and *Keras* libraries, which are standard tools for developing artificial neural network models [17,18]. An MLP was used for the evaluation and obtaining the required results. For the hidden layer, sigmoidal (logistic), hyperbolic tangent (tanh), swish, and ReLU were used as the activation functions. The output neurones predominantly employed a linear activation function. Based on the foregoing and considering the number of data points and their characteristics, various combinations were used within the model code to develop the models. These combinations yielded 44 predictive models. In addition to the activation functions, the data scaling methods, proportions of the training and test datasets, and number of neurones in the hidden layer varied. Calibration (i.e. model training) was performed to identify the optimal model [11,12].

To facilitate a clearer comparison of the performance of the different models, Table 3 presents the best-performing artificial neural network models for each group according to the applied scaling method and activation function.

Table 3. Best artificial neural network model results according to the MAPE criterion [%]

Scaling procedure	**Activation function**	**Number of neurons in hidden layer**	**Training** [%]	**Test** [%]
MinMaxScaler	ReLu	6	8.35	8.06
StandardScaler	ReLu	3	8.45	8.16
MinMaxScaler	Sigmoid	6	8.63	7.96
StandardScaler	Sigmoid	5	8.14	8.21
MinMaxScaler	Swish	3	8.60	8.12
StandardScaler	Swish	6	8.41	8.23
MinMaxScaler	Tanh	7	8.45	8.12

The MAPE was used to assess model accuracy, as it enables the intuitive interpretation of results in percentage terms and is independent of the unit of measurement. This metric is particularly well-suited for the analysis of dam deformations, where displacement values are relatively small, because it enables a direct comparison of model deviations relative to the actual values without being affected by the scale of the observed quantities. The results in Table 3 are presented using the MAPE expressed as a percentage (%), where lower values indicate greater model accuracy. The minimum error in the test set was considered as the reference value for selecting the optimal model, based on which the model quality was assessed. The detailed results for all the analysed models are presented in Table 4. All neural network models (NMC_i, i = 1, 2, ..., 44) consist of three input variables, one hidden layer, and one output variable. The modelling results indicate a satisfactory level of predictive accuracy. For additional visual validation, the measured and predicted values of the radial displacement were compared. As shown in Figure 4, the model successfully captures the overall trend of displacement variations. Certain deviations are observed at extreme values, which is expected owing to the complex influence of thermal and hydraulic factors that are not fully represented in the model. This figure illustrates the model performance at a single measurement location. A similar level of agreement between the predicted and measured values is observed at other measurement locations.

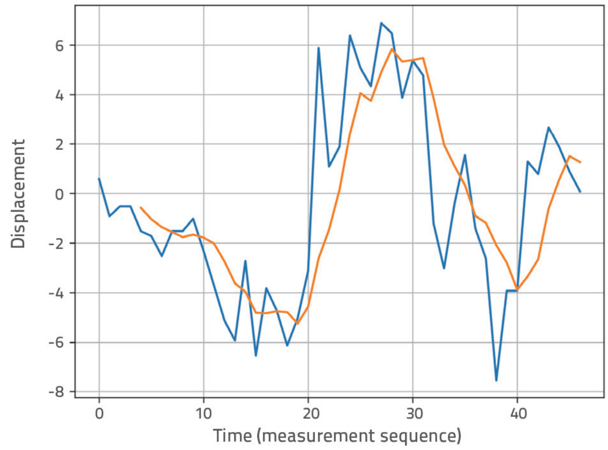

Figure 4. Comparison of the Measured and Predicted Radial Displacements (R5, 678)

Figure 5 shows the typical structure of the MLP neural network used in this study, which consists of three input neurons, one hidden layer, and one output neuron. The network represents a nonlinear regression model capable of approximating complex functional relationships between the input parameters and radial displacement.

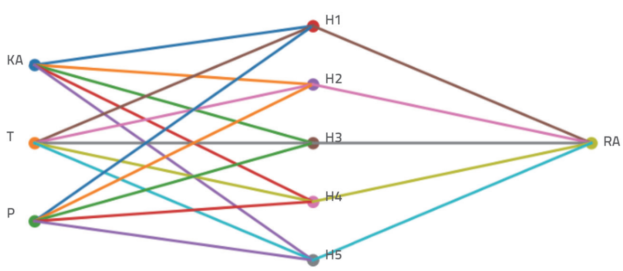

Figure 5. Typical Structure of the Multilayer Perceptron Neural Network (3–5–1 Architecture)

Based on the summarized results presented in Table 4, it can be observed that model NMC 23 achieves the highest prediction accuracy, as determined by the MAPE. The NMC 23 model consists of a three-layer neural network comprising an input layer, a hidden layer (containing five neurons), and an output layer. This model was selected as the final one and served as the basis for the predictive model developed in this study. The observed relationships between the input parameters and radial displacement indicate the dominant influence of the hydrostatic pressure and temperature variations. These findings are consistent with previous studies in which a combination of monitoring data and numerical models was used to identify the principal mechanisms governing dam deformation [13], while the influence of fluid–structure interaction on the system response was also confirmed through dynamic analyses of dams. The application of linear analysis in the present study represents an acceptable simplification that enables a clear assessment of the influence of the dominant parameters on the structural behaviour [14].

Table 4. Overview of the performance of all analysed artificial neural network (MLP) models

Model name	Model characteristics	Training set	Test set
NMC 1	MLP 3-3-1	8.50	8.04
NMC 2	MLP 3-4-1	8.50	8.17
NMC 3	MLP 3-5-1	8.49	8.13
NMC 4	MLP 3-6-1	8.35	8.06
NMC 5	MLP 3-7-1	8.40	7.97
NMC 6	MLP 3-3-1	8.45	8.16
NMC 7	MLP 3-4-1	8.45	8.16
NMC 8	MLP 3-5-1	8.47	8.31
NMC 9	MLP 3-6-1	8.44	8.15
NMC 10	MLP 3-7-1	8.28	8.33
NMC 11	MLP 3-3-1	8.59	8.24
NMC 12	MLP 3-4-1	8.56	8.12
NMC 13	MLP 3-5-1	8.60	8.25
NMC 14	MLP 3-6-1	8.63	7.96
NMC 15	MLP 3-7-1	8.53	8.17
NMC 16	MLP 3-3-1	8.43	8.11
NMC 17	MLP 3-4-1	8.40	8.07
NMC 18	MLP 3-5-1	8.14	8.21
NMC 19	MLP 3-6-1	8.19	8.10
NMC 20	MLP 3-7-1	8.21	8.11
NMC 21	MLP 3-5-1	8.17 (80%)	8.46 (20%)
NMC 22	MLP 3-5-1	8.63 (90%)	7.96 (10%)
NMC 23	**MLP 3-5-1**	**8.34 (90%)**	**7.73 (10%)**
NMC 24	MLP 3-3-1	8.60	8.12
NMC 25	MLP 3-4-1	8.57	8.14
NMC 26	MLP 3-5-1	8.56	8.21
NMC 27	MLP 3-6-1	8.65	8.16
NMC 28	MLP 3-7-1	8.58	8.15
NMC 29	MLP 3-3-1	8.58	8.15
NMC 30	MLP 3-4-1	8.58	8.28
NMC 31	MLP 3-5-1	8.52	8.38
NMC 32	MLP 3-6-1	8.41	8.23
NMC 33	MLP 3-7-1	8.41	8.13
NMC 34	MLP 3-3-1	8.65	8.12
NMC 35	MLP 3-4-1	8.61	8.14
NMC 36	MLP 3-5-1	8.61	8.12
NMC 37	MLP 3-6-1	8.57	8.16
NMC 38	MLP 3-7-1	8.45	8.12
NMC 39	MLP 3-3-1	8.50	7.74
NMC 40	MLP 3-4-1	8.28	8.10
NMC 41	MLP 3-5-1	8.63	7.96
NMC 42	MLP 3-6-1	8.39	8.22
NMC 43	MLP 3-7-1	8.22	8.03
NMC 44	MLP 3-5-1	8.67 (80%)	8.31 (20%)

The obtained results indicate that the structural behaviour can be adequately described using a limited number of dominant parameters, which is consistent with contemporary approaches to dam analysis, where complex systems are reduced to the key components governing their response. Although the actual behaviour of the structure may involve nonlinear effects, linear models are frequently used in engineering practice because they provide a stable and efficient means of assessing the dominant characteristics of the system [15].

The results further confirm that the application of intelligent algorithms enhances the interpretation of monitoring data and facilitates the identification of critical structural conditions, which is consistent with contemporary studies that demonstrate the advantages of combining monitoring technologies with artificial intelligence methods in dam analysis [16].

The prediction presented in this study refers to the estimation of the radial displacement at a selected point on the dam, rather than to the assessment of the overall structural stability or limit states of the system. Sensitivity analysis of the input parameters was not explicitly performed in this study, which represents a limitation of the proposed model and a potential direction for future research. Consequently, it is impossible to precisely determine the confidence interval of the results or quantify the individual contributions of each input parameter to the output variable, which may affect the interpretation of the predictions obtained. This model can be regarded as an empirical regression model based on monitoring data, providing a balance between prediction accuracy and interpretability in engineering practice.

4. Conclusion

This study analysed the radial displacements of the Piva concrete arch dam using long-term monitoring data collected over 48 years of operation. A predictive model based on artificial neural networks was developed using the reservoir water level, temperature, and groundwater level as input parameters.

The results demonstrated that the model reliably approximated the structural behaviour, with the NMC 23 model, having a 3–5–1 architecture identified as the optimal solution. The model achieved an MAPE of 8.34 % for the training dataset and 7.73 % for the test dataset, indicating good generalisation capability and demonstrating its potential applicability in engineering practice.

The application of models based on actual measurements enabled a realistic assessment of structural behaviour, with the effects of long-term processes such as concrete creep and shrinkage implicitly incorporated through historical monitoring data. The results confirmed that a limited number of dominant parameters can be used to describe the complex behaviour of the dam. The developed model can be regarded as a nonlinear regression model that approximates the functional relationship between the input parameters and radial displacement.

It should be noted that a sensitivity analysis of the input parameters was not performed, which is a limitation of the proposed model and provides a direction for further research. Future work should focus on quantifying the influences of individual input parameters and extending the model to other types of structural displacements and additional monitoring variables. The developed model is already being applied in the modernisation of the monitoring system at the "Piva" hydropower plant, where it contributes to the improved interpretation of measurement data and more reliable engineering decision-making.

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