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Modelling of dam behaviour based on neuro-fuzzy identification

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ABSTRACT

The radial displacement of one or several points of the dam is an important time-varying behaviour indicator and it is a nonlinear function of hydrostatic pressure, temperature and other unexpected unknown causes. Nonlinear system identification is becoming an important tool which can be used to time-varying behaviour modelling of engineering structures. Identification and prediction of complex nonlinear structural behaviour are complex tasks for which non-parametric models are often used. The objective of this study is to develop a neuro-fuzzy identification model to predict the radial displacement of the arch dam. The ANFIS (adaptive network-based fuzzy inference system) models were developed and tested using experimental data collected during 11 years. Comparing the values predicted by the ANFIS with the experimental data indicates that soft computing models provide accurate results. These models can be applied for prediction of displacement in further studies.

1. Introduction

Effective dam safety monitoring programs are essential for dams and they are widely accepted. As a part of dam safety programs, instrumentation is installed to measure a particular parameter of interest. These parameters can include water levels, deformations or movements, pressures, loading conditions, temperature variations, seepage flows, seepage water clarity, piezometric levels, etc. The aim of the timely detection of abnormal behaviour of the dam does not necessarily imply frequent monitoring or collection of a great deal of data. It is important that this information is representative and adequately interpreted. Interpretation of the available data is very important for the dam health monitoring.

Variations of hydrostatic pressure and temperature and other unexpected unknown causes, such as results of time effects, are main variables that should be taken into account when analysing the structural response of the dam. Deterministic and statistical methods have been used to develop models to predict the nonlinear structural behaviour of the dam [1]. The hybrid method, which is a combination of the two fundamental methods, has also been applied to forecast behaviour [2]. The deterministic modelling requires solving differential equations for which closed form solutions may be difficult or impossible to obtain [3]. Therefore, numerical methods, such as the finite element method, are used. The advantages of statistical methods, such as multiple linear regression (MLR), are simplicity of formulation and speed of execution. In the MLR model, it is possible to identify the contribution of each loading action to the structural response [4]. In order to correlate the dam behaviour with the intrinsic parameters of the dam, such as structure size, boundary conditions and elastic properties, structural identification techniques are applied to analyse the collected measures, [5–7].

The dam deformation is a typical example of nonlinear time-varying behaviour [8,9]. System identification of concrete dams can be categorised as one of the most significant aspects of dam engineering, [10]. Identification and prediction of the dam deformation are complex tasks for which non-parametric models are often used. Gülal et al. [11] used linear ARX (autoregressive with exogenous inputs) model calculated from a 3D finite element model to assess the impact of horizontal displacements in the dam. The displacement of one or several points of the dam is a nonlinear function of hydrostatic pressure, temperature and other unexpected unknown causes. In the last decade, soft computing techniques have been extensively applied for complex time series prediction. Neural network modelling and identification are effective tools for approximation of uncertain nonlinear dynamic systems. Feedforward and recurrent neural networks have been widely studied in nonlinear systems identification [12–17].

In recent years, Takagi–Sugeno fuzzy systems, as a class of fuzzy models, have been applied as nonlinear system identifiers [18,19]. The Takagi–Sugeno fuzzy model provides satisfactory results in describing behaviour of complex and uncertain systems. Babuška [20] showed an overview of neuro-fuzzy modelling methods for nonlinear system identification.

In the present work, the ANFIS is used for structural identification of the arch dam. The ANFIS, first introduced by Jang [21], is a

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universal approximator and as such is capable of approximating any real continuous function on a compact set to any degree of accuracy [22]. Hamidian and Seyedpoor [23] and Seyedpoor et al. [24] presented an efficient methodology to find the optimal shape of arch dams using an adaptive neuro-fuzzy inference system.

The procedure based on neuro-fuzzy modelling was presented and discussed for the horizontal displacements of an arch dam by Demirkaya [25].

The objective of this study is to develop a neuro-fuzzy identification model for the dam radial displacement prediction and to demonstrate its application to identifying complex nonlinear relationships between the input and output variables. The proposed approach based on the ANFIS identification can be a very helpful tool for modelling of time-varying behaviour of engineering structures.

2. Case study

The Bočac dam, on the Vrbas River, is a medium size dam (Fig. 1). The dam is located in the Republic of Srpska, about 25 km from the city of Banja Luka. The dam was constructed between 1976 and 1981. It is a double curvature arch dam, 66 m high, with 221.4 m long crest. The crest thickness is 3 m while the maximum thickness of the dam base is 14.4 m. The minimum, normal and maximum operating levels are 254, 282 and 283 m above sea level (asl), respectively. The total capacity of reservoir is $52.7 \times 10^6\,\mathrm{m}^3$. The dam is equipped with a monitoring system to measure parameters such as concrete, water and air temperatures, reservoir water level, horizontal and vertical displacements, rotations, movements of joints, strain, stress, uplift pressure, foundation displacements and seepage.

Three pendulums were installed to measure radial and tangentials deformations. In this paper, the radial displacement of the points P1 and P2 at the block 8 is analysed with the proposed method Fig. 2. The data set included 783 data samples. It was divided into training and test sets. The data from January 2000 to December 2008 were used to train, and the data from January 2009 to December 2010 were used to test.

3. ANFIS Identification

A wide class of nonlinear dynamic systems can be described by a nonlinear autoregressive model with exogenous inputs (NARX) [26]. The nonlinear model for prediction of the arch dam radial displacement has two inputs (u_1,u_2) and one output (y_m) and can be described as follows:

$$y_m(k) = f_m(\boldsymbol{\varphi}(k), \boldsymbol{\theta}) \tag{1}$$

where $y_m(k)$ is the output of the model, k is the time instant, $\boldsymbol{\varphi}(k) = (y(k-1), y(k-2), \ldots, y(k-n_y), u_1(k-1), u_1(k-2), \ldots, u_1(k-n_{u_1}), u_2(k-1), u_2(k-2), \ldots, u_2(k-n_{u_2}))$ is the regression vector, $\boldsymbol{\theta}$ is the parameter vector, n_{u_1} and n_{u_2} denote the numbers of the lags of the inputs (u_1,u_2) and n_y denotes the number of the lag of the output (y).

The problem with the nonlinear system identification is to approximate the unknown function f_m in (1) from the sampled data $\{(u_1(k), u_2(k), y(k)) | k = 1, 2, \ldots, N\}$, N is the number of the sample data. The fuzzy systems have the capability of universal approximation, [27,28] and can be employed to perform input–output mapping. In general, there are two types of fuzzy inference models [22]. The Mamdani fuzzy model, in which the antecedent and the consequent are fuzzy propositions, has been used to achieve quantitative analysis [29]. The Mamdani model is typically used in expert systems. The second type of the fuzzy model is the Takagi and Sugeno model [30,31]. In this model, the consequent is an affine linear function of the input variables. When the consequent is constant, a zero order Takagi–Sugeno fuzzy model is formed, which can be considered a special case of the Mamdani fuzzy inference system.

The structure scheme of the Takagi–Sugeno fuzzy system identification is shown in Fig. 3.

The input vector to the Takagi–Sugeno fuzzy system consists of y and u_1 and u_2 which are past values of the output and input, respectively:

$$\begin{aligned} I^T(k) = [&y(k-1), y(k-2), \ldots, y(k-n_y), u_1(k-1), \\ &u_1(k-2), \ldots, u_1(k-n_{u_1}), u_2(k-1), u_2(k-2), \ldots, u_2(k-n_{u_2})] \end{aligned} \tag{2}$$

The output is $y_m(k)$.

It is assumed that the fuzzy inference system under consideration has $n_y + n_{u_1} + n_{u_2} + 1$ variables, $n_y + n_{u_1} + n_{u_2}$ inputs and one output variable. All input linguistic variables are supposed to have the same number of linguistic values, n. Linguistic values of the variable $y(k-j)$ are A_{ij}, $i = 1, n, j = 1, n_y$; $u_1(k-l)$ are B_{il}, $i = 1, n$, $l = 1, n_{u_1}$ and $u_2(k-m)$ are C_{im}, $i = 1, n$, $m = 1, n_{u_2}$.

For the zero-order TS fuzzy model with $n_y + n_{u_1} + n_{u_2}$ inputs and one output, a set of linguistic rules is defined in the form of:

R_1: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and … and $y(k-n_y)$ is A_{1n_y} and $u_1(k-1)$ is B_{11} and $u_1(k-2)$ is B_{12} … and $u_1(k-n_{u_1})$ is $B_{1n_{u_1}}$ and $u_2(k-1)$ is C_{11} and $u_2(k-2)$ is C_{12} … and $u_2(k-n_{u_2})$ is $C_{1n_{u_2}}$ then: $f_1 = \gamma_1$.
R_2: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and … and $y(k-n_y)$ is A_{1n_y} and $u_1(k-1)$ is B_{11} and $u_1(k-2)$ is B_{12} … and $u_1(k-n_{u_1})$ is $B_{1n_{u_1}}$ and $u_2(k-1)$ is C_{11} and $u_2(k-2)$ is C_{12} … and $u_2(k-n_{u_2})$ is $C_{2n_{u_2}}$ then: $f_2 = \gamma_2$.
…
R_q: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and … and $y(k-n_y)$ is A_{2n_y} and $u_1(k-1)$ is B_{21} and $u_1(k-2)$ is B_{22} … and $u_1(k-n_{u_1})$ is $B_{2n_{u_1}}$ and $u_2(k-1)$ is C_{21} and $u_2(k-2)$ is C_{22} … and $u_2(k-n_{u_2})$ is $C_{2n_{u_2}}$ then: $f_q = \gamma_q$.
…
R_p: if $y(k-1)$ is A_{n1} and $y(k-2)$ is A_{n2} and … and $y(k-n_y)$ is A_{nn_y} and $u_1(k-1)$ is B_{n1} and $u_1(k-2)$ is B_{n2} … and $u_1(k-n_{u_1})$ is $B_{nn_{u_1}}$ and $u_2(k-1)$ is C_{n1} and $u_2(k-2)$ is C_{n2} … and $u_2(k-n_{u_2})$ is $C_{nn_{u_2}}$ then: $f_p = \gamma_p$.

where f_q is the consequent function for the rule q, and γ_q is the consequent parameter ($q = 1, p$).

The number of linguistic rules is: $p = n^{(n_y + n_{u_1} + n_{u_2})}$.

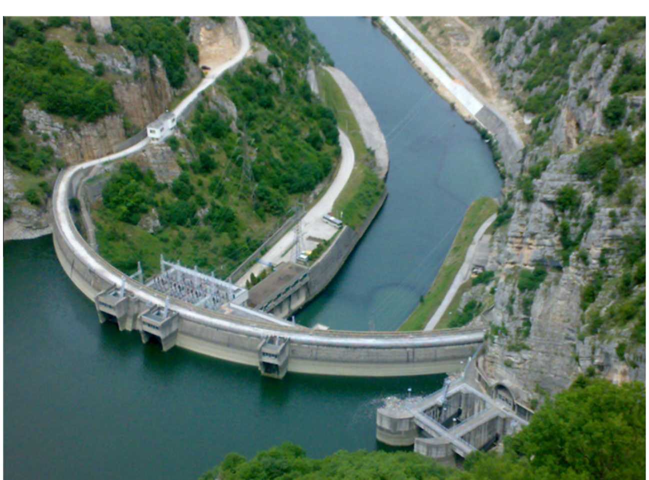

Fig. 1. The view of the Bočac dam.

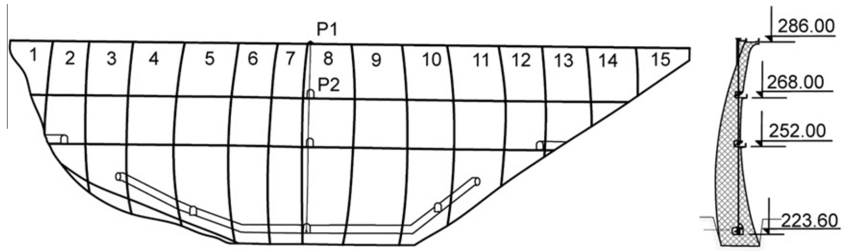

Fig. 2. The upstream face of the dam and the cross-section through the block 8.

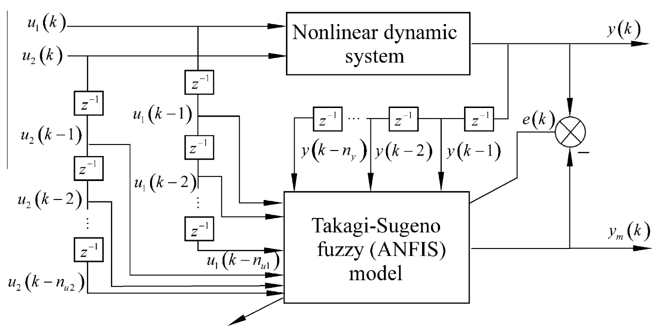

Fig. 3. The block scheme of the Takagi–Sugeno fuzzy model.

The output from Takagi–Sugeno fuzzy system is:

$$y_m(k) = \sum_{q=1}^{p} \bar{z}_q f_q \tag{3}$$

where

$$\bar{z}_q = \frac{z_q}{\sum_{q=1}^{p} z_q} \tag{4}$$

$$\begin{aligned}
z_1 = {} & \mu_{A_{11}}(y(k-1)) * \mu_{A_{12}}(y(k-2)) * \cdots * \mu_{A_{1n_y}}(y(k-n_y)) * \\
& \mu_{B_{11}}(u_1(k-1)) * \mu_{B_{12}}(u_1(k-2)) * \cdots * \mu_{B_{1n_{u_1}}}(u_1(k-n_{u_1})) * \\
& \mu_{C_{11}}(u_2(k-1)) * \mu_{C_{12}}(u_2(k-2)) * \cdots * \mu_{C_{1n_{u_2}}}(u_2(k-n_{u_2})) \\
z_2 = {} & \mu_{A_{11}}(y(k-1)) * \mu_{A_{12}}(y(k-2)) * \cdots * \mu_{A_{1n_y}}(y(k-n_y)) * \\
& \mu_{B_{11}}(u_1(k-1)) * \mu_{B_{12}}(u_1(k-2)) * \cdots * \mu_{B_{1n_{u_1}}}(u_1(k-n_{u_1})) * \\
& \mu_{C_{11}}(u_2(k-1)) * \mu_{C_{12}}(u_2(k-2)) * \cdots * \mu_{C_{2n_{u_2}}}(u_2(k-n_{u_2})) * \\
& \ldots \\
z_q = {} & \mu_{A_{21}}(y(k-1)) * \mu_{A_{22}}(y(k-2)) * \cdots * \mu_{A_{2n_y}}(y(k-n_y)) * \\
& \mu_{B_{21}}(u_1(k-1)) * \mu_{B_{22}}(u_1(k-2)) * \cdots * \mu_{B_{2n_{u_1}}}(u_1(k-n_{u_1})) * \\
& \mu_{C_{21}}(u_2(k-1)) * \mu_{C_{22}}(u_2(k-2)) * \cdots * \mu_{C_{2n_{u_2}}}(u_2(k-n_{u_2})) \\
& \ldots \\
z_p = {} & \mu_{A_{n_1}}(y(k-1)) * \mu_{A_{n2}}(y(k-2)) * \cdots * \mu_{A_{nn_y}}(y(k-n_y)) * \\
& \mu_{B_{n1}}(u_1(k-1)) * \mu_{B_{n2}}(u_1(k-2)) * \cdots * \mu_{B_{nn_{u_1}}}(u_1(k-n_{u_1})) * \\
& \mu_{C_{n1}}(u_2(k-1)) * \mu_{C_{n2}}(u_2(k-2)) * \cdots * \mu_{C_{nn_{u_2}}}(u_2(k-n_{u_2}))
\end{aligned}$$

$*$ denotes a certain T-norm.

If the membership function is taken in the Gaussian form, then:

$$\mu_{A_{ij}}(y(k-j)) = \exp\left(\frac{-0.5\left(y(k-j) - c_{A_{ij}}\right)^2}{\sigma^2_{A_{ij}}}\right), \quad i = 1, n;\ j = 1, n_y \tag{5}$$

$$\mu_{B_{il}}(u_1(k-l)) = \exp\left(\frac{-0.5(u_1(k-l) - c_{B_{il}})^2}{\sigma^2_{B_{il}}}\right), \quad i = 1, n;\ l = 1, n_{u_1} \tag{6}$$

and

$$\mu_{C_{im}}(u_2(k-m)) = \exp\left(\frac{-0.5(u_2(k-m) - c_{C_{im}})^2}{\sigma^2_{C_{im}}}\right),$$
$$i = 1, n;\ m = 1, n_{u_2} \tag{7}$$

$c_{A_{ij}}$, $\sigma_{A_{ij}}$, $c_{B_{il}}$, $\sigma_{B_{il}}$, $\sigma_{C_{im}}$, $c_{C_{im}}$ are the parameter of the function $\mu_{A_{ij}}$, $\mu_{B_{il}}$ and $\mu_{C_{im}}$. These are the premise parameters.

Consequence functions of the qth fuzzy rules are of the form:

$$f_q = \gamma_q \tag{8}$$

Substituting (4), (8) and into (3), the system output is obtained as:

$$y_m(k) = \frac{1}{\sum_{q=1}^{p} z_q} \sum_{q=1}^{p} z_q \gamma_q \tag{9}$$

This system is called the adaptive neuro-fuzzy inference system (ANFIS) [21].

The difference between the output of the plant $y(k)$ and the output of the network $y_m(k)$ is called the prediction error:

$$e(k) = y(k) - y_m(k) \tag{10}$$

This error is used to adjust the parameters in the neuro-fuzzy system via the minimisation of the following cost function:

$$\varepsilon = \frac{1}{2} \sum_{k=1}^{N} [y(k) - y_m(k)]^2 \tag{11}$$

The gradient descent method is used for adapting premise parameters. The least squares method is used for updating the consequent parameters. Each epoch of the hybrid learning algorithm involves a forward pass and a backward pass in the ANFIS. Jang [21] described mathematical background of the hybrid learning algorithm.

4. Simulation results and discussion

The major objective of the study presented in this paper is to construct ANFIS models to predict the radial displacement of arch dam.

The selection of an appropriate set of input variables during the ANFIS development is important for modelling. The hydrostatic pressure and the thermal load are the main components to be taken into account when modelling the dam displacement. The hydrostatic load can be accurately modelled on the basis of the reservoir water level. Description of the thermal load requires a detailed knowledge of the temperature values at several points of the structure [5]. This level of knowledge is usually not available. Then, the thermal load can be represented by the parameter d. While suggesting the model for the horizontal displacements of an arch dam, Demirkaya [25] chose the following input variables: the water level of the reservoir, the values of the thermometer embedded in the upstream and downstream face and in the middle of the dam and the air temperature.

The dam displacement is a typical example of time-varying behaviour. In this study, two ANFIS models have been developed for computing the radial displacement of points P1 and P2 at block 8, 2. The inputs of the model are $u_1 = d = \frac{2\pi j_d}{365}$, $u_2 = h$ and the measured horizontal displacement values at previous time steps, where d is the season varying between 0 and 2π, j_d represents the number of days since January 1st, and h is the water level. The range of the input variable h is between 271.88 and 282.22 m. The MATLAB Fuzzy Toolbox is used for the implementation of the fuzzy model.

The number of the ANFIS input is determined by the input and output lags, n_{u_1}, n_{u_2} and n_y, respectively. Prior knowledge, insight in the process behaviour and the purpose of modelling are sources of information for the choice of the possible number of lags [20]. In this study, the satisfactory accuracy is obtained for $n_{u_1} = 1$, $n_{u_2} = 1$ and $n_y = 3$ for both models. The input vector to the Takagi–Sugeno fuzzy systems is:

$$I^T(k) = [y(k-1), y(k-2), y(k-3), u_1(k-1), u_2(k-1)]$$

The predicted value of the radial displacement at time step k depends on the measured values of the radial displacement at time steps $k-1$, $k-2$ and $k-3$ ($y(k-1)$,$y(k-2)$,$y(k-3)$), the water level value and value of the parameter d at time step $k-1$. The effects of the hydrostatic pressure and thermal load on the dam displacements are taken into account in two ways: explicitly through the parameters d and h as inputs and implicitly through the measured values of the radial displacement as inputs into the model. Therefore, the impact of each variable on the model output cannot be considered separately.

The time effect is incorporated into the model by including the measured values of the radial displacement at previous time steps as inputs into the model. These measured values depend not only on variations of the hydrostatic pressure and temperature, but also on other causes including degradation of material properties during the structure lifetime.

Selection of parameters for the training process and their impact on the ANFIS have been addressed in the literature [21]. The initial step size is defined to 0.01. The step size decrease rate is 0.9 and the step size increase rate is 1.1. Fuzzy partitioning of the input variables of the ANFIS is realised by selection of the two primary fuzzy sets.

The two-sided Gaussian (*gauss2mf*) membership function is taken. The function *gauss2mf* $\mu_{A_{ij}}(y(k-j))$ is a combination of two Gaussian functions. The first function, specified by $\sigma_{A_{ij(1)}}$ and $c_{A_{ij(1)}}$, determines the shape of the left-most curve. The second function specified by $\sigma_{A_{ij(2)}}$ and $c_{A_{ij(2)}}$, determines the shape of the right-most curve. Whenever $c_{A_{ij(1)}} < c_{A_{ij(2)}}$, the *gauss2mf* function reaches a maximum value of 1. Otherwise, the maximum value is less than one.

The parameters of the membership functions of the input models for the radial displacement prediction of the points P1 and P2 after training are shown in Tables 1 and 2. For adapting premise parameters (40), the gradient descent method is used. The least squares method is used for updating the consequent parameters (32).

The consequent parameters of fuzzy models $\boldsymbol{\gamma} = [\gamma_1\ \gamma_2 \ldots \gamma_{32}]^T$ are shown in Table 3.

Table 1
The parameters of the membership functions of the input models for the radial displacement prediction of the point P1.

Input variable	Range	Membership function	Parameters of the membership functions
$y(k-1)$	[−4.6 19]	A_{11}	$\sigma_{A11(1)} = 4.009$; $c_{A11(1)} = -11.68$; $\sigma_{A11(2)} = 4.349$; $c_{A11(2)} = 2.666$
		A_{21}	$\sigma_{A21(1)} = 4.683$; $c_{A21(1)} = 11.67$; $\sigma_{A21(2)} = 4.009$; $c_{A21(2)} = 26.08$
$y(k-2)$	[−4.6 19]	A_{12}	$\sigma_{A12(1)} = 4.009$; $c_{A12(1)} = -11.68$; $\sigma_{A12(2)} = 4.318$; $c_{A12(2)} = 2.644$
		A_{22}	$\sigma_{A22(1)} = 4.413$; $c_{A22(1)} = 11.81$; $\sigma_{A22(2)} = 4.009$; $c_{A22(2)} = 26.08$
$y(k-3)$	[−4.6 19]	A_{13}	$\sigma_{A13(1)} = 4.009$; $c_{A13(1)} = -11.68$; $\sigma_{A13(2)} = 6.389$; $c_{A13(2)} = 3.486$
		A_{23}	$\sigma_{A23(1)} = 6.15$; $c_{A23(1)} = 10.95$; $\sigma_{A23(2)} = 4.009$; $c_{A23(2)} = 26.08$
$d(k-1)$	[0.08575 6.26]	B_{11}	$\sigma_{B11(1)} = 1.049$; $c_{B11(1)} = -1.767$; $\sigma_{B11(2)} = 1.572$; $c_{B11(2)} = 2.52$
		B_{21}	$\sigma_{B21(1)} = 0.07908$; $c_{B21(1)} = 4.321$; $\sigma_{B21(2)} = 1.049$; $c_{B21(2)} = 8.112$
$h(k-1)$	[271.9 282.2]	C_{11}	$\sigma_{C11(1)} = 1.756$; $c_{C11(1)} = 268.8$; $\sigma_{C11(2)} = 2.749$; $c_{C11(2)} = 275.9$
		C_{21}	$\sigma_{C21(1)} = 2.298$; $c_{C21(1)} = 278.9$; $\sigma_{C21(2)} = 1.756$; $c_{C21(2)} = 285.3$

Table 2
The parameters of the membership functions of the input model for the radial displacement prediction of the point P2.

Input variable	Range	Membership functions	Parameters of the membership function
$y(k-1)$	[2.1 17.5]	A_{11}	$\sigma_{A11(1)} = 2.616$; $c_{A11(1)} = -2.52$; $\sigma_{A11(2)} = 2.763$; $c_{A11(2)} = 7.707$
		A_{21}	$\sigma_{A21(1)} = 1.703$; $c_{A21(1)} = 10.77$; $\sigma_{A21(2)} = 2.616$; $c_{A21(2)} = 22.12$
$y(k-2)$	[2.1 17.5]	A_{12}	$\sigma_{A12(1)} = 2.616$; $c_{A12(1)} = -2.52$; $\sigma_{A12(2)} = 1.98$; $c_{A12(2)} = 6.994$
		A_{22}	$\sigma_{A22(1)} = 0.9371$; $c_{A22(1)} = 13.93$; $\sigma_{A22(2)} = 2.616$; $c_{A22(2)} = 22.12$
$y(k-3)$	[2.1 17.5]	A_{13}	$\sigma_{A13(1)} = 2.616$; $c_{A13(1)} = -2.52$; $\sigma_{A13(2)} = 3.491$; $c_{A13(2)} = 8.029$
		A_{23}	$\sigma_{A23(1)} = 4.369$; $c_{A23(1)} = 13.15$; $\sigma_{A23(2)} = 2.616$; $c_{A23(2)} = 22.12$
$d(k-1)$	[0.08575 6.26]	B_{11}	$\sigma_{B11(1)} = 1.049$; $c_{B11(1)} = -1.767$; $\sigma_{B11(2)} = 4.589$; $c_{B11(2)} = 3.609$
		B_{21}	$\sigma_{B21(1)} = 0.7791$; $c_{B21(1)} = 2.377$; $\sigma_{B21(2)} = 1.049$; $c_{B21(2)} = 8.112$
$h(k-1)$	[271.9 282.2]	C_{11}	$\sigma_{C11(1)} = 1.756$; $c_{C11(1)} = 268.8$; $\sigma_{C11(2)} = 1.718$; $c_{C11(2)} = 276.4$
		C_{21}	$\sigma_{C21(1)} = 1.833$; $c_{C21(1)} = 281.5$; $\sigma_{C21(2)} = 1.756$; $c_{C21(2)} = 285.3$

Table 3
The consequent parameters of the fuzzy models.

ANFIS model point P1	$\boldsymbol{\gamma}$ = [−10.05 −1.035 −3.234 0.2076 34.11 7.047 44.67 6.528 6.528 −6.504 −30.79 12.88 47.52 21.54 27.61 11.22 45.57 −4.537 −20.93 −5.292 −81.12 29.12 15.05 31.25 13.13 −11.43 11.87 −9.628 18.2 19.39 19.5 19.43]^T
ANFIS model point P2	$\boldsymbol{\gamma}$ = [−171.1 −41.32 173.8 52.15 150.4 −39.14 −117.6 59.66 −41.91 97.45 73.06 −70.96 14.88 −8.423 33.56 38.7 169.4 −50.56 −144.3 61.11 −220.1 49.29 232.8 −16.49 16.78 1.356 −8.53 1.138 16.65 17.47 15.21 15.32]

The ANFIS models in the considered examples have 32 rules:

R_1: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_1 = \gamma_1$.
R_2: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_2 = \gamma_2$.
R_3: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_3 = \gamma_3$.
R_4: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_4 = \gamma_4$.
R_5: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_5 = \gamma_5$.
R_6: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_6 = \gamma_6$.
R_7: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_7 = \gamma_7$.
R_8: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_8 = \gamma_8$.
R_9: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_9 = \gamma_9$.
R_{10}: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_{10} = \gamma_{10}$.
R_{11}: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_{11} = \gamma_{11}$.
R_{12}: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_{12} = \gamma_{12}$.
R_{13}: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_{13} = \gamma_{13}$.
R_{14}: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_{14} = \gamma_{14}$.
R_{15}: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_{15} = \gamma_{15}$.
R_{16}: if $y(k-1)$ is A_{11} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_{16} = \gamma_{16}$.
R_{17}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_{17} = \gamma_{17}$.
R_{18}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_{18} = \gamma_{18}$.
R_{19}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_{19} = \gamma_{19}$.
R_{20}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_{20} = \gamma_{20}$.
R_{21}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_{21} = \gamma_{21}$.
R_{22}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_{22} = \gamma_{22}$.
R_{23}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_{23} = \gamma_{23}$.
R_{24}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{12} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_{24} = \gamma_{24}$.
R_{25}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_{25} = \gamma_{25}$.
R_{26}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_{26} = \gamma_{26}$.
R_{27}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_{27} = \gamma_{27}$.
R_{28}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{13} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_{28} = \gamma_{28}$.
R_{29}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{11} then: $f_{29} = \gamma_{29}$.
R_{30}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{11} and $h(k-1)$ is C_{21} then: $f_{30} = \gamma_{30}$.
R_{31}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{11} then: $f_{31} = \gamma_{31}$.
R_{32}: if $y(k-1)$ is A_{21} and $y(k-2)$ is A_{22} and $y(k-3)$ is A_{23} and $d(k-1)$ is B_{21} and $h(k-1)$ is C_{21} then: $f_{32} = \gamma_{32}$.

The prediction performances of the soft computing models were evaluated using the correlation coefficient (r), the mean absolute error (MAE) and the mean square error (MSE):

$$r = \frac{\sum_{k=4}^{N}(y_m(k) - \bar{y}_m)(y(k) - \bar{y})}{\sqrt{\sum_{k=4}^{N}(y_m(k) - \bar{y}_m)^2 \sum_{k=4}^{N}(y(k) - \bar{y})^2}} \tag{12}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=4}^{N}|y_m(k) - y(k)| \tag{13}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=4}^{N}(y_m(k) - y(k))^2 \tag{14}$$

where y_m and y denote the model output and the measured value, respectively; $\bar{y}_m$ and $\bar{y}$ denote their average values, respectively, and N represents the number of observations.

Smaller MAE and MSE values ensure better performance.

The performance parameters of the ANFIS models for the radial displacement prediction are given in Table 4.

The NARX model assumes that the observations are sampled with the same frequency. In our simulation, the training data set was complete. Many techniques for the estimation of missing data can be applied even if the training data set is not complete [32]. In the case when the model is used and there is no measured displacement value $y(k-i)$, the estimated value $y_m(k-i)$ can be used.

Figs. 4 and 5 show measured and model computed values of the radial displacement of the points P1 and P2 in the training and test sets.

The errors between the measured and modelled values of the radial displacement of the points P1 and P2 are shown in Fig. 6. The input variable d of the proposed ANFIS model is not continuous (on December 31 its value is 2π and on January 1st it is 0). The error diagrams (Fig. 6) show that there is no significant difference between the observed and modelled values on these days, because the effects of the thermal load on the dam displacements are taken in account explicitly through the parameters d as input and implicitly through the measured values of the radial displacement as inputs into the model.

The results of this study can be compared with the results reported in the literature.

Mata [4] compared multiple linear regression and multilayer perceptron neural network models for the prediction of the upstream–downstream displacement of the arch dam recorded by a pendulum. The models were generated on the basis of experimental data on time histories of reservoir levels, external temperatures and structural responses. The correlation coefficient for values obtained by the multiple linear regression model and the observed dam displacement values were 0.97 and 0.98 for the training and test sets, respectively. The same correlation coefficient of 0.98 was calculated between the measured and neural network modelled values for the training and test sets.

Both statistical analysis and structural identification were applied to the three dams for prediction of the horizontal upstream–downstream crest displacement by De Sortis [5]. The correlation coefficients from 0.877 to 0.983 were reported between the measured and values estimated with the statistical analysis. Authors concluded that the structural identification technique

Table 4
Performance parameters of the ANFIS models for the radial displacement prediction of the points P1 and P2.

Model	Data set	r	MAE	MSE
ANFIS model point P1	Training	0.9888	0.6811	0.7908
	Test	0.9832	0.8937	1.3142
ANFIS model point P2	Training	0.9815	0.5241	0.4555
	Test	0.9712	0.7035	0.7456

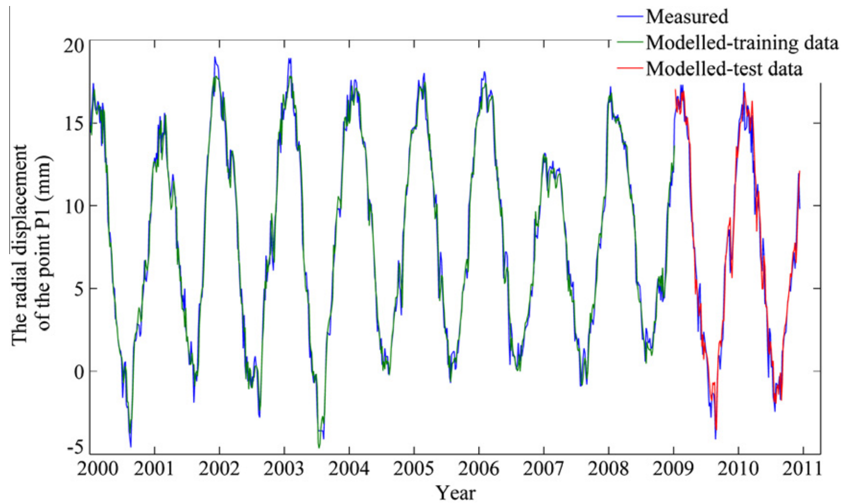

Fig. 4. Measured and model computed values of the radial displacement of the point P1 in the training and test sets.

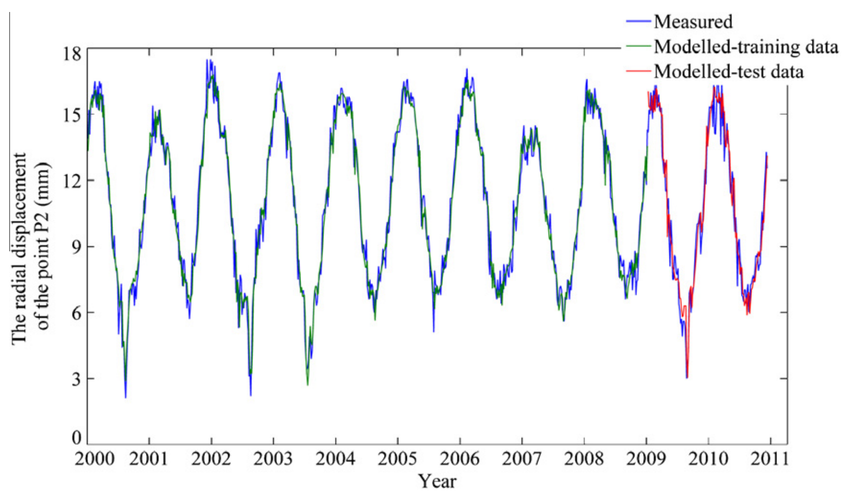

Fig. 5. Measured and model computed values of the radial displacement of the point P2 in the training and test sets.

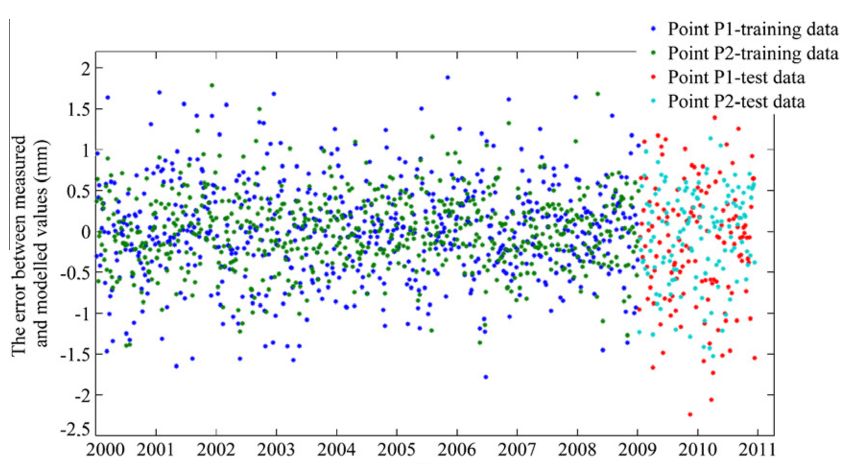

Fig. 6. The errors between the measured and model computed values of the radial displacement.

provides higher degree of accuracy in predicting the future behaviour of the structure. The correlation coefficient for modelled values and observed values ranged from 0.933 to 0.988.

Demirkaya [25] developed three ANFIS models for displacement forecasting. The best ANFIS model has coefficients of correlation values for the training and test sets of 0.9936 and 0.9996, respectively. The daily recorded data from January 1992 to December 1998 are used for the training and test of the models.

In our study, the proposed neuro-fuzzy identification model shows efficiency in forecasting the radial displacement, and it is in accordance with results of other authors. The prediction performances of the ANFIS identification models trained and tested with 783 data samples are presented in Table 4. The influence of the frequency measurements on the performance of the models was investigated by construction of new models on a 15-day measurement basis. In the training process, the ANFIS 216 samples were used. For the first ANFIS model, the coefficient of correlation values for the training and test sets were 0.9924, 0.9712, respectively. The correlation coefficient of 0.9866 for the training and 0.9628 for the test set were obtained for the second ANFIS model. The decrease in the measurement frequency yields models with a slightly higher coefficient of correlation values for the training set, but a slightly lower coefficient of correlation values for the test set.

5. Conclusion

The prediction of the future dam displacements is a challenging problem in dam engineering. The behaviour of a dam is a nonlinear function of hydrostatic pressure, temperature and other unexpected unknown causes such as the result of time effects. This paper studies identification of nonlinear structural behaviour using the ANFIS. Comparison between the modelled radial displacement values obtained by the ANFIS and the experimental data shows that neuro-fuzzy identification can be an effective tool for the approximation of uncertain nonlinear structural behaviour of the arch dam. The performance of the soft computing models were tested using correlation coefficients, the mean absolute error and the mean square error.

The main limitation of this approach lies in the fact that it does not directly consider mechanical properties and possible damage. Additional analysis in the form of non-destructive tests (statical and dynamical), computational mechanical modelling and inverse analysis are also required.

Our further investigation will be directed towards possible applications of the proposed approach based on the ANFIS identification for the computation of seepage, stress and crack opening of a dam. Once developed, the fuzzy logic model can be used for further monitoring activities, as a predictive management tool.

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