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DEVELOPMENT OF NEURO-FUZZY MODEL FOR DAM SEEPAGE ANALYSIS

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Abstract: Modeling seepage through geological formations located near the dam site or dam bodies is a challenging task in dam engineering. In order to monitor the seepage, piezometric devices are installed on sections of the dam. The objective of this study is to develop a neuro-fuzzy model to predict the water level in piezometers of the Iron Gate 2 dam. The neuro-fuzzy model was developed using experimental data which was collected during a period of nine years. The measurements of tailwater level taken on the same day, one day before, and two days before the measurements of piezometer were input variables, and the water level in the examined piezometer was the target output in the neuro-fuzzy model. The measured data has been compared with the results of neuro-fuzzy model on the basis of correlation coefficient (r), coefficient of determination (R^2), mean square error (MSE) and mean absolute error (MAE). Comparing the experimental data with the values modeled by the neuro-fuzzy system indicates that the computational intelligence models provide very accurate results.
Keywords: Dam, Seepage, Piezometric water level, Neuro-fuzzy system

1. INTRODUCTION

Dam parameters monitoring through installed instrumentation is the most important part of a dam safety program [1]. These parameters might include displacement, strain, stress, pressure, loads on structural members, seepage, temperature, reservoir level and precipitation, etc. Timely and accurate analysis and prediction of the dam behaviour indicators is an essential part of the dam safety control.

Different models have been developed and used to analyze dam behaviour. These are grouped into two general categories: deterministic and statistical models, [2]. The deterministic modeling requires solving differential equations for which closed form solutions may be difficult or impossible to obtain, [3]. The advantages of the statistical method, such as multiple linear regression, consist in simplicity of formulation and speed of execution. Modeling seepage through geological formations located near the dam site or dam bodies is an important dam engineering task. Artificial intelligence technique often generates simple solution for nonlinear problems in accurate forecasting of the dam behaviour indicators.

Nourani and Babakhani [4] supposed integration of artificial neural networks with radial basis function for interpolation in earthfill dam seepage modeling. Artificial neural networks and the Box Jenkins approach are used for seepage control in earth dams by Carvalho, Gutiérrez and Romanel, [5]. Tayfur et al., [6] employed a finite element method and three layer neural network model to simulate flow through earthfill dam. Results of the simulations show that the neural network model performed as good as and in some cases better than the finite element method model. Peng and Tian [7] presented and established neural network model to prediction of seepage quantities of the dam foundation. In order to predict water level in piezometers, Ranković et al. [8] developed an artificial neural network model and used the tailwater levels taken on the same day, 1 day before and 2 days before the measurements taken by piezometers as the input variables.

The aim of this paper is to construct an neuro-fuzzy model to predict water levels in piezometers. The neuro-fuzzy is proved to be universal approximator of the nonlinear multi-input and single output function.

2. CASE STUDY

Iron Gate 2 dam was built in 1984 as a joint-venture between the governments of Serbia and Romania, to serve both countries in the production of electricity. The dam is equipped with a monitoring system to measure a particular parameters, such as: concrete, water and air temperatures, reservoir water level, horizontal and vertical displacements, rotations, foundation displacements, movements of joints, strain, stress, uplift pressure, foundation displacements and seepage. In this paper, the piezometric water level is analysed with the proposed method. The data collected from January 1997 to November 2005 were used for training and testing neural networks, Figure 1.

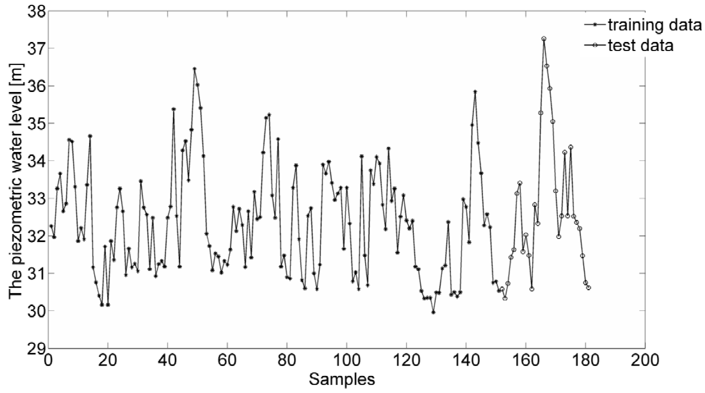

Figure 1. Measured values of the water level of the piezometer in the training and test sets

3. NEURO-FUZZY MODEL TO PREDICT PIEZOMETRIC WATER LEVEL

In this study, the neuro-fuzzy model is used to predict the piezometric water level. The input variables of the neuo-fuzzy model were: measurements of tailwater level taken on the same day (ht_1), one day before (ht_2), and two days before (ht_3) the measurements of piezometer. The water level in a piezometer is the output variable (hp). The neuro-fuzzy system [9] used in this paper is shown in Figure 2.

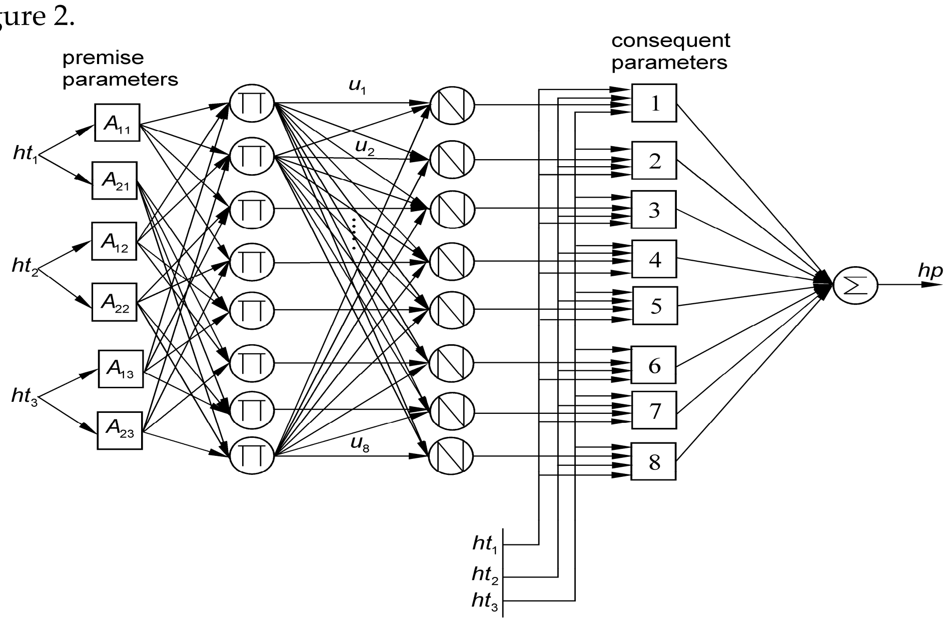

Figure 2. Structure of neuro-fuzzy model to predict the piezometric water level.

The rule base contains 8 rules, with 2 membership functions A_{ij} being assigned to each input variable. The rule base of the neuro-fuzzy system is:

$$R_1: \text{If } ht_1 \text{ is } A_{11} \text{ and } ht_2 \text{ is } A_{12} \text{ and } ht_3 \text{ is } A_{13} \text{ then } f_1 = p_{11}ht_1 + p_{12}ht_2 + p_{13}ht_3 + c_1$$

$$R_2: \text{If } ht_1 \text{ is } A_{11} \text{ and } ht_2 \text{ is } A_{12} \text{ and } ht_3 \text{ is } A_{23} \text{ then } f_2 = p_{21}ht_1 + p_{22}ht_2 + p_{23}ht_3 + c_2$$

$$R_3: \text{If } ht_1 \text{ is } A_{11} \text{ and } ht_2 \text{ is } A_{22} \text{ and } ht_3 \text{ is } A_{13} \text{ then } f_3 = p_{31}ht_1 + p_{32}ht_2 + p_{33}ht_3 + c_3$$

R_4: If ht_1 is A_{11} and ht_2 is A_{22} and ht_3 is A_{23} then $f_4 = p_{41}ht_1 + p_{42}ht_2 + p_{43}ht_3 + c_4$

R_5: If ht_1 is A_{21} and ht_2 is A_{12} and ht_3 is A_{13} then $f_5 = p_{51}ht_1 + p_{52}ht_2 + p_{53}ht_3 + c_5$

R_6: If ht_1 is A_{21} and ht_2 is A_{12} and ht_3 is A_{23} then $f_6 = p_{61}ht_1 + p_{62}ht_2 + p_{63}ht_3 + c_6$

R_7: If ht_1 is A_{21} and ht_2 is A_{22} and ht_3 is A_{13} then $f_7 = p_{71}ht_1 + p_{72}ht_2 + p_{73}ht_3 + c_7$

R_8: If ht_1 is A_{21} and ht_2 is A_{22} and ht_3 is A_{23} then $f_8 = p_{81}ht_1 + p_{82}ht_2 + p_{83}ht_3 + c_8$

where p_{kj} and c_k; $k = 1,2,\dots,8,\ j = 1,2,3$ are the consequent parameters.

The output of the neuro-fuzzy can be presented as:

$$hp = \frac{1}{\sum_{k=1}^{8} u_k} \sum_{k=1}^{8} u_k \left(\sum_{j=1}^{3} p_{kj} ht_j + c_k \right) \tag{1}$$

where:

$$u_1 = \mu_{A_{11}}(ht_1) * \mu_{A_{12}}(ht_2) * \mu_{A_{13}}(ht_3),\ u_2 = \mu_{A_{11}}(ht_1) * \mu_{A_{12}}(ht_2) * \mu_{A_{23}}(ht_3),\ u_3 = \mu_{A_{11}}(ht_1) * \mu_{A_{22}}(ht_2) * \mu_{A_{13}}(ht_3)$$

$$u_4 = \mu_{A_{11}}(ht_1) * \mu_{A_{22}}(ht_2) * \mu_{A_{23}}(ht_3),\ u_5 = \mu_{A_{21}}(ht_1) * \mu_{A_{12}}(ht_2) * \mu_{A_{13}}(ht_3),\ u_6 = \mu_{A_{21}}(ht_1) * \mu_{A_{12}}(ht_2) * \mu_{A_{23}}(ht_3)$$

$$u_7 = \mu_{A_{21}}(ht_1) * \mu_{A_{22}}(ht_2) * \mu_{A_{13}}(ht_3),\ u_8 = \mu_{A_{21}}(ht_1) * \mu_{A_{22}}(ht_2) * \mu_{A_{23}}(ht_3)$$

$*$ denotes T-norm.

If the Gaussian membership function is taken $\mu_{A_{ij}}\left(ht_j\right)$ is given by:

$$\mu_{A_{ij}}\left(ht_j\right) = e^{\frac{-\left(ht_j - c_{ij}\right)^2}{2\sigma_{ij}^2}},\ i = 1,2,\ \ j = 1,2,3 \tag{2}$$

where: c_{ij} and σ_{ij} are the parameters of the membership function or premise parameters.

In this paper the hybrid learning algorithm that combines the gradient descent and the least-squares estimate method is used for updating the parameters. For adapting premise parameters gradient descent method is used. The least squares method is used for updating the consequent parameters.

4. SIMULATION RESULTS

The neuro-fuzzy system is used the piezometric water level. The MATLAB Fuzzy Toolbox is applied for the implementation of the fuzzy system. The prediction performances of the neuro-fuzzy model were evaluated using correlation coefficient (r), mean absolute error (MAE) and mean square error (MSE), Table 1.

Table 1. Performance parameters of the neuro-fuzzy models for prediction of the piezometric water level.

Data set	r	MAE	MSE
Training	0.981	0.2094	0.0762
Test	0.988	0.2392	0.0965
Training + Test	0.982	0.2144	0.0795

In this example, the total number of the fitting parameters is composed of 12 premise parameters and 32 consequent parameters. The Gaussian membership function is taken. The parameters of the membership functions of the inputs model to predict the piezometric water level after training are shown in Table 2.

Table 2. The parameters of the membership functions of the input model for prediction of the piezometric water level

Input variable	Mem. func.	Parameters of the membership functions
ht_1	A_{11}	$\sigma_{A11} = 2.177$; $c_{A11} = 27.2$
	A_{21}	$\sigma_{A21} = 1.067$; $c_{A21} = 34.93$
ht_2	A_{12}	$\sigma_{A12} = 1.835$; $c_{A12} = 28.98$
	A_{22}	$\sigma_{A22} = 1.831$; $c_{A22} = 37.52$
ht_3	A_{13}	$\sigma_{A13} = 1.361$; $c_{A13} = 29.7$
	A_{23}	$\sigma_{A23} = 3.106$; $c_{A23} = 37.32$

5. CONCLUSION

The prediction of the future water level in piezometers is a challenging problem in dam engineering. This paper studies prediction of water level in piezometers. The performance of the neuro-fuzzy models was tested using correlation coefficients, the mean absolute error and the mean square error.

Comparison between the modeled piezometric water level values obtained by the neuro-fuzzy and the experimental data shows that neuro-fuzzy can be an effective tool for prediction water level in piezometers, and therefore predicting the extent of seepage from the dam and its surroundings. From a practical point of view, neuro-fuzzy are able to detect anomalous seepage and hence to develop immediate remedial measures.

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