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Comparison between Neural Networks and Adaptive Neuro-fuzzy Inference System in Modeling Lake Kerkini Water Level Fluctuation Lake Management using Artificial Intelligence

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ABSTRACT

This study presents lake Kerkini water level simulation. Water level depends on a large number of parameters and procedures which are usually complex or non-linear. Water level was calculated, by using a model based on visual basic language. The model took account of all parameters that contribute to water level. Simulation was achieved when the model output approximated the available measured values. Afterwards, the same project was implemented by using artificial intelligence methods. These are, artificial neural networks and adaptive neuro fuzzy inference system. The basic advantage of this implementation is the fact that the output is obtained without having to use all the parameters that contribute to the final result. This means that they can be implemented for modeling systems where the procedures are not fully known or when there is a large parameter number affecting the result. Both models showed a great performance in simulating water level fluctuation and they are also suggested for prediction.

Key words: Fuzzy logic, neural networks, prediction, lake modeling, hydrology

INTRODUCTION

Water resources management has been playing an increasing role over the last decades in human effort for sustainable development. It is a particularly complex decision making environment that is sensitive to engineering, social and economic constraints. In such projects, water cycle knowledge is essential in order to quantify the hydrologic response of a catchment in terms of surface runoff. This information is necessary for the selection and design of the appropriate water management and for every hydraulic work design. This process is usually very complex. Due to the high heterogeneity and non-linearity of the elements constituting the water cycle, a physical description is difficult to achieve. Usually sophisticated mathematical tools are required, a significant amount of calibration data and some degree of expertise and experience with the model. ArtificialIntelligent (AI) represents a machine's ability to emulate human behavior. It does not use complex rules and mathematical routines but approaches the answer through a procedure that resembles human reasoning. Artificial intelligence techniques find application in most of the fields of human knowledge and have been used widely over the last decades to model natural systems. Two of the most popular concepts in the area of AI are neural networks and fuzzy logic systems. They have proven to be effective tools in handling complex or non linear physical problems, even when the system understanding is incomplete. The basic advantage is the fact that there is no need to know accurately the physical processes of a natural system. They both belong to the data-driven techniques, which means that the aim when implementing these methods is to find the interactions between inputs and outputs, train the system and give the result.

Artificial Neural Networks (ANN) have an ability to identify underlying, highly complex relationship from input-output data in the form of a black box. Artificial Neural Networks are able to overcome the limitations of the conventional approaches by extracting the desired information directly from the data. They have been used in river flow forecasting (Aqil *et al.*, 2007; Gopakumar *et al.*, 2007; Firat and Turan, 2010), rainfall-runoff modeling (Antar *et al.*, 2006), water level fluctuations (Altunkaynak, 2007).

Fuzzy Logic (FL) method was first developed by Zadeh (1965) to describe human thinking in mathematical terms. Fuzzy logic models have been applied in water movement (Bardossy and Disse, 1993), in the description of the elements of the hydrological cycle (Bardossy, 1996), in reservoir operation (Russell and Campbell, 1996; Shrestha *et al.*, 1996; Panigrahi and Mujumdar, 2000; Li-Chiu and Fi-John, 2001), in forecasting (Pongracz *et al.*, 1999; Abebe *et al.*, 2000; Mahabir *et al.*, 2003; Nayak *et al.*, 2005) and others.

In this study the ability of modeling lake Kerkini water level fluctuation is investigated, using artificial neural networks and an adaptive neuro-fuzzy inference system. The results are compared to the observed values.

ANFIS (ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM)

The most common method to deal with the uncertainties was probability theory, until 1965, when Zadeh introduced the fuzzy set theory. Fuzzy logic is an effective tool for handling the ambiguity and uncertainty of the real world systems. The Fuzzy Rule-Based (FRB) systems or Fuzzy Inference Systems (FIS) originate from fuzzy logic and generally the fuzzy set theory. FRB systems provide an effective way to capture the approximate nature of the real world processes, due to the rule formulation. A collection of fuzzy IF-THEN rules constitutes a fuzzy rule-based system or a fuzzy inference system. First the input variables, which are usually crisp, are being transformed into fuzzy ones, by applying a membership function. This procedure describes the degree to which an input value belongs to a fuzzy set. The membership functions can take many forms, but the most common are the triangular ones. The fuzzy premises are connected using operators (AND, OR and rarely XOR). AND is the most commonly used operator, corresponding to the intersection of the classical sets. There are many ways to interpret the AND operator, defined by a great variety of t-norms, as they have been proposed by many researchers. The implementation of a t-norm (or a t-conorm, when variables are connected with OR) results to Degree of Fulfillment (DOF) of a rule, which also takes values from the [0, 1] interval (Tzimopoulos *et al.*, 2008).

ANFIS is a technique for constructing fuzzy inference systems and was proposed by Jang (1993). The ANFIS is a multilayer self-organized network structure that adapts parameters of the fuzzy system to predict the system output. It works like neural networks and it is able to learn from a data set the membership function parameters in order to capture the system behaviour. These parameters are being adjusted during the training process in order to obtain the IF-THEN rules. The data set consists of input and output values. A gradient vector facilitates the computation of these parameters. Once the gradient vector is obtained, any of the several available optimization routines can be applied in order to adjust the parameters and reduce the model error. ANFIS is based on Takagi-Sugeno (Zimmermann, 2005) inference systems and its architecture is as follows:

Suppose a rule system consisting of two fuzzy premises x and y and one response. The model includes the following two fuzzy "If-Then" rules:

Rule 1: IF x is A_1 and y is B_1 Then $f_1 = p_1x + q_1y + r_1$
Rule 2: IF x is A_2 and y is B_2 Then $f_2 = p_2x + q_2y + r_2$

- **Layer 1:** Every node has a membership function:

$$O_{i,1} = \mu_{A_i}(x)$$

where, x is the input to node i, A_i a linguistic variable and i_{Ai} the membership function. $O_{i,1}$ specifies the degree to which the given x satisfies the quantifier A_i. If the bell-function is applied then:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right] b_i}$$

where, $\{a_i, b_i, c_i\}$ the parameter set.

- **Layer 2:** The results of the previous layer are combined in order to produce the Degree of Fulfillment (DOF) for each rule. When the AND operator is used, then a t-norm is applied. The Algebraic product is selected from the available t-norms because it shows the best performance as obtained from past research (Tzimopoulos *et al.*, 2008):

$$O_{i,2} = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), \quad i = 1,2$$

- **Layer 3:** In this layer, the i-th node calculates the ratio of the i-th rule's DOF to the sum of all rules DOF 's:

$$O_{i,3} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2$$

- **Layer 4:** Every node i in this layer is a node with a function:

$$O_{i,4} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

where, $\{p_i, q_i, r_i\}$ the parameter set.

- **Layer 5:** The deffuzification procedure is applied:

$$O_{i,5} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

The above equations describe an adaptive network which is functionally equivalent to a Sugeno first-order fuzzy inference system. The learning rule specifies how the premise parameters and consequent parameters should be updated to minimize a prescribed error measure E. ANFIS possesses good capability of learning, constructing, expanding and classifying. It has the advantage of allowing the extraction of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base. It can also adapt the complicated conversion of human intelligence to fuzzy systems.

ARTIFICIAL NEURAL NETWORKS

An ANN is a computer model composed of individual processing elements called units or nodes. They are highly interconnected and operate in parallel. These elements are inspired by biological nervous systems. Within the human brain, individual cells, referred to as neurons, undertake discrete computations in a massively parallel system. Neurons are responsible for the human capacity to learn and this significant property is used in machine learning in artificial neural networks. An ANN emulates this computational capacity by distributing computations to several interconnected layers of simple processing units known as artificial neurons.

Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Neural networks are good at fitting functions, recognizing patterns and clustering data (Demuth *et al*., 2007).

A neural network structure in a simple form consists of three layers. The first one is the input layer, which is used to present data to the network, the output layer, which is used to produce an appropriate response to the given input and one or more intermediate layers (hidden), which are used to act as a collection of feature detectors, in order to derive the result that is closer to the output. There can be several hidden layers between input and output layers. The hidden layers increase the network's ability to model more complex events.

The network-layered structure consists of a set of nodes (neurons) connected by links from one layer to its next layer (Fig. 1). Each link is assigned a weight, which is a numerical estimate of the connection strength. The knowledge is stored in the connection strengths or synaptic weights of the interconnected adjoining layers. A layer includes the combination of the weights, the multiplication and summing operation (here realized as a vector product Wp), the bias b and the transfer function f. The weighted summation of inputs to a node is converted to an output according to a transfer function (usually a sigmoid one). Each node in a layer receives and processes weighted input from a previous layer and transmits its output to nodes in the following layer through links. The main advantage of the feed forward architecture is that it requires relatively low amounts of computing time during training. Therefore, this network is valuable for evaluating the network performance when numerous simulations are necessary (Martin *et al*., 2005).

Sigmoid transfer function: This transfer function is commonly used in backpropagation networks, because it is differentiable and continuous, as shown in Fig. 2. The output of neuron j is given by:

$$y_j = \frac{1}{1 + e^{(-v_j)}}$$

Levenberg-Marquardt training method: Training is the procedure where the weights and biases are modified in order to improve system performance. The ANN is capable of learning the

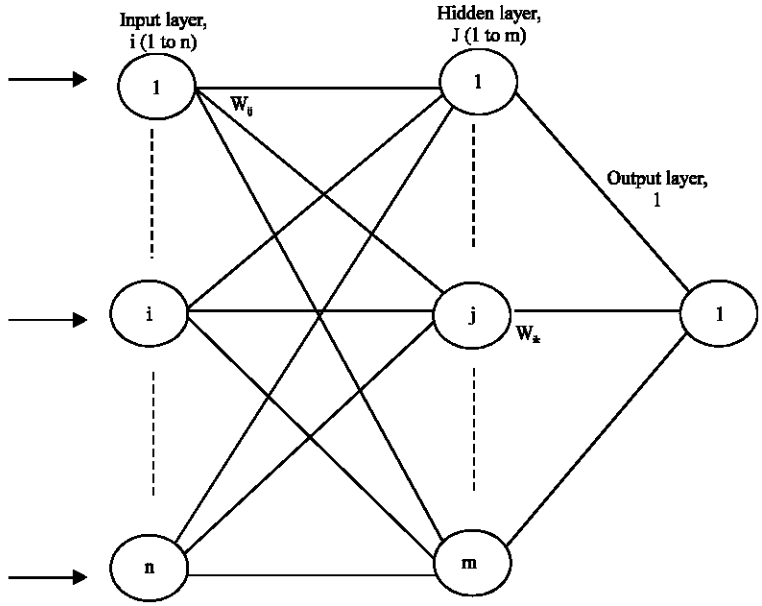

Fig. 1: The network-layered structure

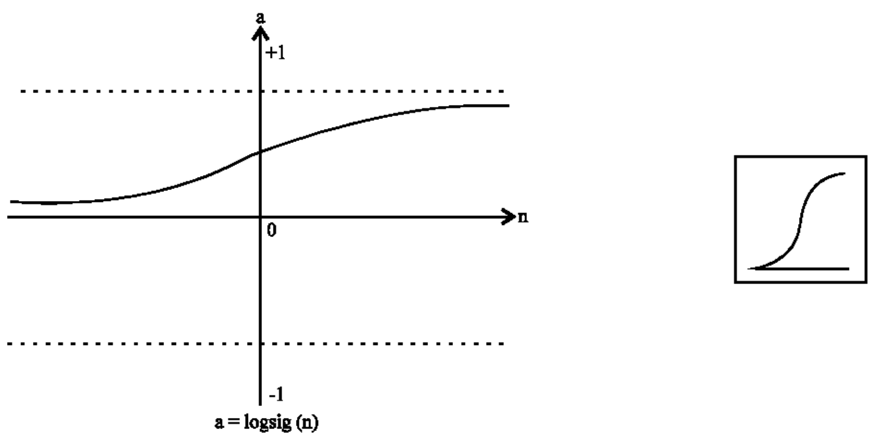

Fig. 2: The Sigmoid transfer function shape

relationships from the available data, which consist the training set. The network learns the values of the internal parameters of the model. The learning process involves comparing the model forecast with the known correct answer and adjusting of synaptic weights based on a selected learning rule to minimize the network error. If a backpropagation procedure is applied then the error is passed to each node and the appropriate weight changes are made, in order to achieve the closest to the output value.

Levenberg-Marquardt is the fastest method to train a neural network. It was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as:

$$H = J^T J$$

and the gradient can be computed as:

$$g = J^T e$$

where, J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$g = J^T e x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm (Demuth *et al.*, 2007).

Study area: The project was performed at the Aristotle University of Thessaloniki in 2009. The available data cover a time period from 1982 to 2003.

The Strymonas River basin (Fig. 3) is a transboundary basin shared by Greece (36.5%), FYROM (95%), Serbia (4%) and Bulgaria (50%). The Greek part of the basin covers an area of 6.472 km^{-2} (Life Environment Strymon, 2007). Strymonas River and Lake Kerkini (an artificial lake fed by Strymonas) are the main surface water bodies in the basin which in turn support the natural enrichment of the basin with groundwater. The length of the river in Greece is 121 km and the mean annual inflow discharge from Bulgaria is 75 $m^3 sec^{-1}$. Strymonas outflows to Strymonikos Gulf, whose coastal ecosystems are very important for fisheries, biodiversity and tourism.

Lake Kerkini (N: 41° 12', E: 23° 09') is a reservoir situated about 100 km to the north of Thessaloniki city. Lake Kerkini was transformed into a reservoir in 1932 by the construction of a dam. This was designed to provide irrigation water for cultivation (maize, rice, etc.) on the Serres plain downstream and also for flood control. The height at the top of the dyke was then +33 m above sea level (asl). Following siltation by river sediments, which led to 61% loss of the storage capacity of the reservoir and an increase in the area of land to be irrigated by the reservoir (from 13,500 ha in 1970 to 32,600 ha in 1990), it proved necessary to build a new, higher dam and a new dyke to the west at a height of +39 m asl. The existing dyke also had to be raised to reach a height of +39 m asl. This new dam was inaugurated in 1982 and a further raising of the dykes to +41 m asl was planned. (Crivelli *et al.*, 1995).

Application

Modelling Strymonas hydrological basin: In order to evaluate Strymonas basin water budget, the available data (rainfall, temperature etc.) were collected from years 1982 to 2003, which is also

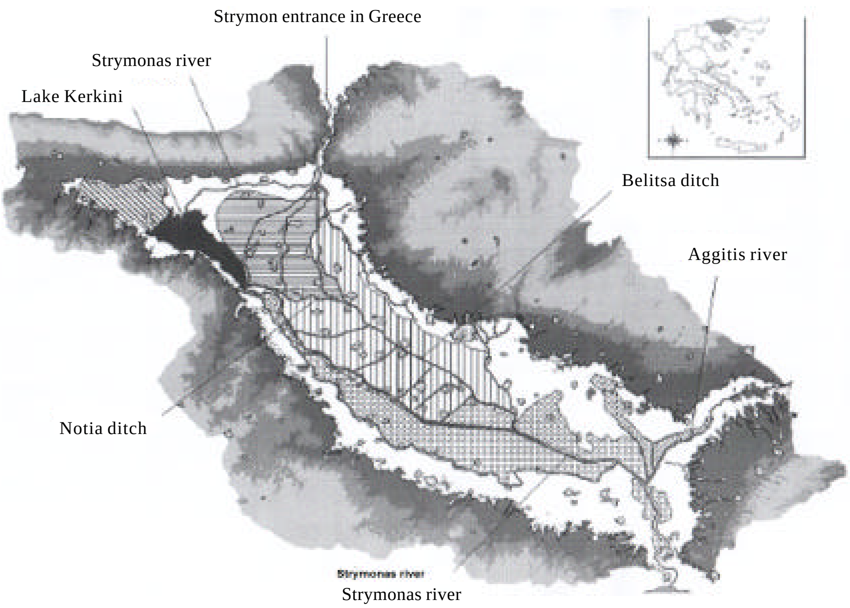

Fig. 3: Strymonas river basin

the study period (Antonopoulos *et al.*, 2001). There are 8 available meteorological stations in the study area. Where it was needed, missing data records were calculated using statistical methods and highly correlated data from neighboring stations.

Lake Kerkini water level values were not available from 1990 to 2003. In order to obtain these values, a program constructed by the authors in Visual Basic language was used. This program performs a water budget calculation for the whole basin, using system analysis. Program outputs are Lake Kerkini water level and runoff. Program inputs were rainfall, lake evaporation, Strymonas basin evaportanspiration, water flow from Bulgaria and water consumption that comes from human activities.

The greek part of Strymonas basin was digitized and divided into 17 sub-basins. For each one, according to the vegetation and the mean hill slope, different infiltration coefficients were assigned. This means that runoff was calculated initially for each sub-basin separately.

Rainfall heights were computed for each sub-basin using the kriging method, were the punctual information obtained from meteorological stations is transformed to the surface.

Evapotranspiration is a factor that affects water budget significantly. Usually empirical formulae are used to estimate the amount of water that corresponds to evapotranspiration. In this project the Turc method was used (Alley, 1984).

On the other hand, evaporation from the lake was calculated using the Thornwaite method (Thornthwaite, 1948) which was proposed to estimate potential evapotranspiration. The results were compared to the observed values of Iraklia evaporimeter and were quite satisfactory. In particular the correlation coefficient between observed and calculated evaporation values was $R^2 = 0.8507$ and the Mean Square Error (MSE) equals to 0,2505.

The simulation period was from 1982 to 2003 and the criterion for model calibration was Lake Kerkini water level, since calculated values were compared to the measured ones (years 1982 to 1989). Figure 4 shows the observed values from years 1982 to 1989 and the calculated values from 1982 to 2003. It can be seen that the model approaches the calculated values sufficiently.

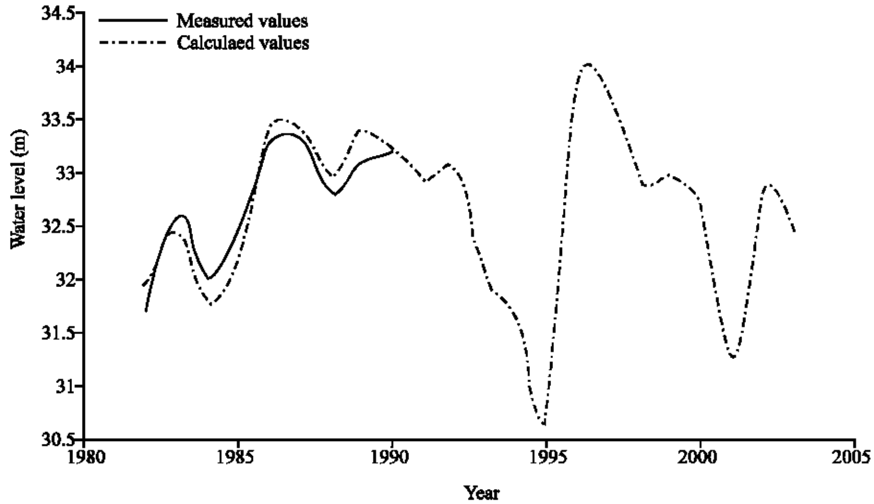

Fig. 4: Observed values from years 1982 to 1989 and calculated values from 1982 to 2003

ANFIS for modelling lake Kerkini: The input variable selection is the most critical procedure and demands a good knowledge of the system to be modelled. It has been shown that model performance is significantly increased, when the correlation between inputs and outputs is high (Tzimopoulos *et al.*, 2008). Model performance was tested using different combinations of input variables. Finally, rainfall and evapotranspiration were used as fuzzy premises and water level as fuzzy response. The number of membership functions to divide the domain of the fuzzy premises was also one of the parameters investigated. Several numbers of triangular fuzzy sets were used, varying from 2 to 10, through a trial and error procedure. The best model performance was achieved using three and four fuzzy sets for rainfall and evapotranspiration, respectively.

ANFIS model was executed twice (ANFIS 1 and ANFIS 2 models), testing the implementation of the proper *t-norm* (Zimmermann, 2005). First it was executed using product function to calculate the Degree of Fulfillment of each rule (ANFIS 1 model). This method takes under consideration the membership function of every input consisting a rule, in order to calculate the DOF. Afterwards the model was tested again using the "min" function to derive the DOF (ANFIS 2 model). In this case the DOF is equal to the minimum of the membership functions corresponding to the inputs.

The entire set of observations was divided into a training and validation set. The training set is used when the rules cannot be directly formulated by the experts and is used to learn them. The validation set is implemented for measuring the performance of the rule system. Monthly data from the years 1982 to 1997 were used for training the models and the years 1998 to 2003 for validating them.

ANN for modelling lake Kerkini: The Levenberg-Marquardt training method was used because it is fast and it has a better performance (Aqil *et al.*, 2007). The available data were divided into three parts: The training data set (years 1982 to 1997), the testing data set (years 1998 to 2000) and the verification data set (years 2001 to 2003).

Sigmoid function was used as the activation function for the hidden and output layer neurons. The optimum number of hidden layers was found by a series of trials and through a sensitivity analysis. Five hidden layers were finally applied. Too small number of hidden layers leads to insufficient degrees of freedom and the model is unable to capture all relations between variables. On the other hand, too many hidden layer neurons will make the model overfit. As a symptom the model memorizes certain cases, loses its ability to generalize and has a poor performance in the verification.

Model evaluation criteria: The performance of both models was assessed using the reduced Mean Squared Error (Reduced MSE) and the correlation coefficient R between the observed and calculated values. The Reduced-MSE is given by the following equation:

$$\text{Reduced MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{Y_{obs} - Y_{calc}}{Y_{obs}}\right)^2$$

where, Y_{obs} is the observed value, Y_{calc} the calculated value from the model.

CONCLUSION

The applicability of the neural network and adaptive neuro-fuzzy inference system in modelling the lake water-level changes was examined in this study. In general, all models are able to give quick and satisfactory answers to practical problems. This is the main advantage of AI techniques, where there full knowledge of the system to be modelled is not a prerequisite.

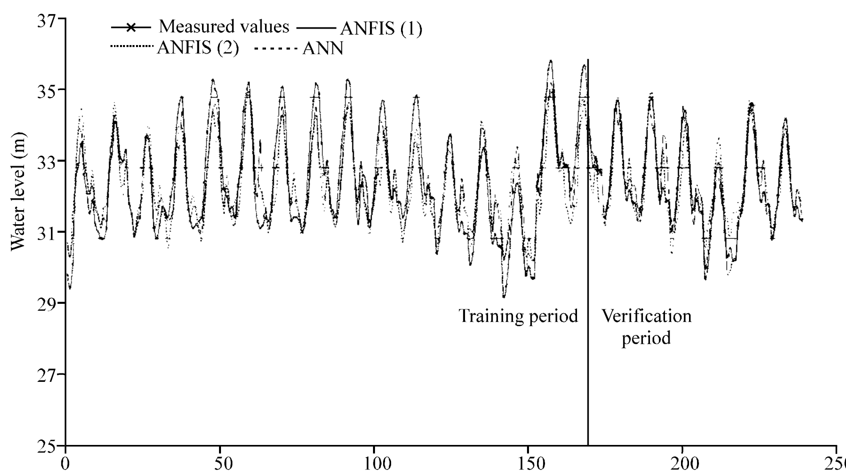

Fig. 5: Fuzzy logic and artificial neural network model performance

Table 1: Statistical parameters for ANFIS 1 model

Data set	R^2	Reduced MSE
Training (1982-1997)	0.8435	0.000275
Verification (1998-2003)	0.8651	0.000301

Table 2: Statistical parameters for ANFIS 2 model

Data set	R^2	Reduced MSE
Training (1982-1997)	0.748	0.000339
Verification (1998-2003)	0.8036	0.000539

Table 3: Statistical parameters for ANN model

Data set	R^2	Reduced MSE
Training (1982-1997)	0.7445	0.000349
Testing (1998-2000)	0.8034	0.000507
Verification (2001-2003)	0.8354	0.000582

The performance of all the models is measured by means of the reduced MSE and the correlation coefficient. ANFIS 1 model performs better in the training and verification period than the other two models. The "product" method for extracting the DOF of each rule gives flexibility to the model. On the contrary, ANFIS 2 model which is based on the "min" inference method approaches measured values less efficiently. The ANN model has the same performance with the ANFIS 2 model for training and testing-verification. Finally it has to be noted that all models show some difficulty in approaching the extreme values. In Fig. 5 are shown the results using ANFIS 1 and the ANN model. Table 2-3 show the values of the mean square error and the correlation coefficient, after model execution, for ANFIS 1, ANFIS 2 and ANN models, respectively.

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