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RESEARCH ARTICLE

Prediction of Millers Ferry Dam Reservoir Level in USA Using Artificial Neural Network

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Abstract

Reservoir level modeling is important for the operation of dam reservoir, design of hydraulic structures, determining pollution in reservoir and the safety of dam. In this study, daily reservoir levels for Millers Ferry Dam on the Alabama River in USA were predicted using artificial neural networks (ANN). Bayesian regularization backpropagation training algorithm is employed for optimization of the network. The results of the optimal ANN models were compared with conventional auto-regressive models (AR), auto-regressive moving average (ARMA), multi-linear regression (MLR) models. The models are compared with each other according to the three criteria, namely, mean square errors, mean absolute relative error and correlation coefficient. The comparison results show that the ANN models perform better than the conventional models.

Keywords

Reservoir level · prediction · artificial neural network · auto-regressive moving average

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1 Introduction

Reservoir level is a complex index of natural water exchange within their watersheds. Longterm level fluctuations in natural (unregulated) lakes and large dam reservoirs also reflect climate change occurring in the region. Dams are also the most important fresh water sources and their construction is very expensive. Reservoir level fluctuations are also important not only in the planning, designing, and operating the fresh water reservoir made for any purpose (i.e. domestic, industrial, hydropower, and irrigation water supply as well as flood control, navigation, and water quality and quantity improvement) but also in all hydraulic structures. Therefore, they must be well planned and operated for the maximum return benefits. Level measurements or their future equally likely replicas obtained through a estimation model are a direct way of obtaining lake management decision variable. Although it is possible to identify sophisticated models taking into consideration the hydrological and hydro meteorological parameters such as the precipitation, runoff, humidity and temperature, it is economically preferred if a model that simulates the level variations on the basis of past level records is at the hand of the decision maker whether he/she be administrator, local authority or a technical operator (Sen et al. [1]).

Reservoir water level forecasting at various time intervals using the records of past time series is an important issue in water resources planning (engineering, etc.). Variations in reservoir level are complex outcomes of many environmental factors, such as precipitations, direct and indirect runoffs from neighbor catchments, evaporation from free water body, air and water temperature, and interactions between the reservoir and the low lying aquifers. Although it is possible to identify sophisticated models taking into consideration the aforementioned parameters, it is preferable that a model which simulates lake-level variations based on previously recorded lake levels be available for research as well as practical purposes.

Recently, the use of artificial intelligence (AI) methods such as artificial neural networks (ANNs), adaptive neuro-fuzzy has been accepted as an appropriate tool for modeling complex nonlinear phenomena in hydrology and water resources systems, leading to widening of their applications. In this context, AI methods have been widely applied. Recent investigations showed that the ANNs could be successfully used in modeling water resource variables (e.g., ASCE [2], Kisi [3–5]; Wu and Chau [6]). A review of all ANN studies in water resources engineering is beyond the scope of this paper and therefore only some most relevant studies is addressed here. Jain et al. [7] used ANN for predicting reservoir inflow and operations. Deo and Naidu [8] applied ANNs method for wave forecasting. More and Deo [9] used ANNs in wind forecasting. Makarynskyy et al. [10] used ANN in predicting hourly sea-level variations for the following 24 h as well as for half-daily, daily, 5-daily, and 10-daily average sea levels. Ondimu and Murase [11] applied ANN for forecasting reservoir level. Makarynska and Makarynskyy [12] used ANN in predictimg hourly sea-level variations with warning times from 1 to 5 days. Cimen and Kisi [13] used SVM and ANN models in modeling lake-level fluctuations. Unes [14] used ANN model for predicting reservoir level fluctation. Unes [15] predicted plunging depth of density flow in dam reservoir using the ANN technique.

The present study investigates the abilities of ANN and conventional auto-regressive (AR), autoregressive moving average (ARMA), multi-linear regression (MLR) techniques to forecast daily reservoir levels in different lag time steps. The subsequent parts of this paper are organized as follows; the second section deals with describing the used dataset as well as the applied ANN technique. The third part describes the applied statistical measures for model analysis, followed by the fourth section including results and discussions. Finally, the last section gives the concluding remarks of the present study.

2 Materials and methods

2.1 Case study

In this study, daily time-series data of reservoir level records of Millers Ferry Dam station (Station No. 02427505, Latitude 32°06'02", longitude 87°23'57" operated by the US Geological Survey, USGS) on Alabama River at the California in USA were used (Fig. 1). The drainage area at this site is 20.637 mi^2 (square miles). The gauging station datum is 40 m above sea level. For this station, daily time series of lake levels were downloaded from the web server of the USGS.

The Alabama River which is 318-mile long originates north of Montgomery from the confluence of the Coosa River and the Tallapoosa River near the Fall Line. The Fall Line is the boundary between the East Gulf Coastal Plain and provinces of the Appalachian Highlands Region. As with most of the great rivers of Alabama, dams slow the progress of the Alabama River as it flows to meet the Tombigbee River and it forms the Mobile River.

All of the Alabama River is commercially navigable. The Alabama Scenic River Trail is a 631-mile boating trail from Weiss Lake down the Coosa River into the Alabama River.

Data sample consists of 6 years (from 1 October 2006 to 19 December 2012) of daily reservoir level records. For each model, the first 1461 daily levels data were used for training, the remaining 811 daily levels data were used for testing. Table 1 represents the statistical parameters of used data during the study period.

2.2 Artificial Neural Networks (ANNs)

The ANN models are derived from the parallel information architectures found in the brain neuron systems. Rumelhart et al. [16] developed a theoretical framework for neural network. One specific advantage of an ANN compared to traditional methods is that it is not dependent on the complexity or the phenomenon structure. Hence, ANN can be used to solve complex non-linear problems. The complex non-linear problems have a lot of different input parameters and varying scale and boundary conditions. In the executing of an ANN, the observed data set are divided into two groups as the training and testing data. Multilayer perceptrons (MLP) are feed-forward networks with one hidden layer and back-propagation algorithm (BPA) (see Fig. 2). The inputs used in this study are daily reservoir levels and reservoir level recorded at lag time ($L_{t-1} \dots L_{t-5.}$). The output indicates the monthly reservoir level at time L_t. W_{ij} are associated weights; and B is the bias terms. MLP can occur on more than one hidden layer, although theoretical works have shown that a single hidden layer is sufficient for an ANN to approximate any complex nonlinear function (Kisi [17], Cybenco [18], Hornik et al. [19]). Since selection of an appropriate number of hidden layer nodes is important to obtain better network performance, after many trials, the most appropriate hidden layer was selected. A large number of hidden nodes may cause over fitting and is computationally unattractive. In contrast, a small number may be inadequate to learn the input-output relationship (Eberhart and Dobbins [20]). The first stage in the procedure is feed-forward phase, where the input values are associated through weights with the hidden layer. The subsequent stage is back-propagation phase, which adjust weights based on difference between the prediction and observation.

Bayesian regularization technique is used in the training of the MLPs. The technique updates the weights and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. This Bayesian regularization takes place within the Levenberg-Marquardt algorithm. Detailed information about the Bayesian regularization technique and Levenberg-Marquardt algorithm are available in the literature [3,17,20–23]. Further details about ANNs can be found in Bishop [24] or Haykin [25].

2.3 Autoregressive Moving Average (ARMA) Models

ARMA$[p, q]$ (autoregressive moving average) models (Box and Jenkins [26]) use a weighted linear combination of previous

Fig. 1. **a)** Millers Ferry Dam map **b)** Location of Millers Ferry Dam in USA

Tab. 1. Statistical parameters of applied data set during the study period.

Period	Number of patterns	Statistical parameters of recorded data				
		X_{max}	X_{min}	X_{mean}	S_x	C_{sx}
Training	1461	24.6	23.5	24.3	0.247	-1.472
Testing	811	24.6	23.8	24.3	0.126	-0.937

Xmean Xmax, Xmin, S_X, CV and CSX denote the mean, maximum, minimum, standard deviation and skewness coefficient, respectively.

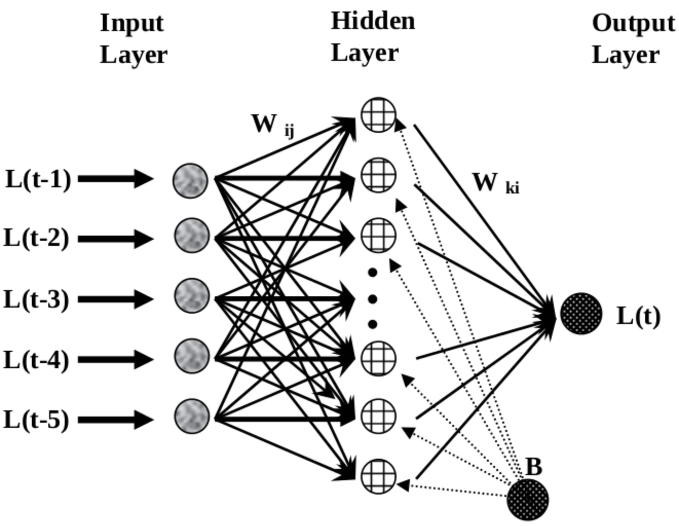

Fig. 2. Artificial neural network structure used in this study

values and shocks which can be written as:

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} \ldots + \varphi_{t-p} y_{t-p} + \ldots + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} \ldots + \theta_{t-p} a_{t-p} \quad (1)$$

where y_t is the predicted value, a_i's are the residuals, and φ_i's and θ_i's are the weights associated with each previous observation and shock respectively. The $[p, q]$ notation indicates the number of autoregressive and moving average terms in the model. The Box-Jenkins method, provides a systematic iterative approach to determine the optimal number of terms and sets varying weights until an optimal weight set is discovered. Standard ARMA models were fitted to the reservoir level data using software developed and supplied with Masters' textbook on time series prediction (Masters [27]) In this paper, models ARMA(1, 1)…ARMA(5,5) have been applied to reservoir level data by using MATLAB.

2.4 Autoregressive (AR) Models

The autoregressive (AR) model of an order p can be written as AR(p) and is defined as

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} \ldots + \varphi_{t-p} y_{t-p} + z_t \quad (2)$$

where z_t is a purely random process; and $E(z_t) = 0$, $Var(z_t) = \sigma_z^2$. The parameters $\varphi_{1.}$,…, φ_p are called the AR coefficients. The name "autoregressive" comes from the fact that X_t is regressed on the its past values. In this paper, models AR(1)…AR(3) have been applied to reservoir level data by using MATLAB. The Yule-Walker equation was used to estimate AR coefficients.

2.5 Multi-Linear Regression (MLR) Model

MLR is used to model the linear relationship between a dependent variable and one or more independent variables. It is also used to (understand which among the independent variables are related to the dependent variable, and to) determine the forms of these relationships. The MLR method is generally based on least squares: the model is fit such that the sum-of-squares of differences of actual and forecasted values is minimized. In this model, the values of the independent variable x is associated with the values of the dependent variable y. Although dam reservoir density flow problems are a nonlinear problem, statistical MLR model is developed to compare the other models. If there are m independent variables and one dependent variable, the multi-linear regression equation can be generally obtained as,

$$y = a + b_1 x_1 + b_2 x_2 + \ldots + b_m x_m + e \quad (3)$$

Where y is a linear combination of the parameters, b_m's are the constants of regression equation, e refers the residual term, and the subscript i indexes a particular observation. The training and testing data groups used for the models are also used for MLR models. For each model, mean square error (MSE) and mean absolute error (MAE) are computed as follows

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(Yi_{observed} - Yi_{forecast} \right)^2 \quad (4)$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left| Yi_{observed} - Yi_{forecast} \right| \quad (5)$$

Where, N and Y_i denote the number of data sets and dam reservoir level, respectively.

3 Application and Results

The present study aims to forecasting of reservoir level fluctuations by ANN, MLR, AR and ARMA models. Several input combinations are constructed to forecast reservoir levels based on partial autocorrelation function analysis (see Fig. 3). L_t represents the daily lake levels at the time t. The input combinations present the previously recorded daily lake levels (L_{t-5}, L_{t-4}, L_{t-3}, L_{t-2}, and L_{t-1}).

The correlation analysis is employed for selecting appropriate input vectors. The autocorrelation (AC) and partial autocorrelation (PAC) statistics and the corresponding 95% confidence bands from lag 0 to lag 14 are estimated for the daily reservoir level time series (Fig. 3).

The AC function describes the correlation between all the pairs of points in the reservoir level time series. As it can be seen from Fig. 3 that the lake-level values are moderately auto correlated. The slower water exchange in reservoir leads to inertia of the water levels. This produces a low frequency oscillation component. A PAC refers the AC of a series with itself under stationary conditions, while controlling for the intervening lags' effect. The precise AC of a series with itself without the confounding effects of intervening lagged AC is showed by PAC (Mutlu et al. 2008). The PAC function indicates significant correlation up to lag 5 and, thereafter, fell within the confidence limits. The rapid decaying pattern of the PAC confirms the dominance of the autoregressive process, relative to the moving average process. The PAC coefficients suggest the incorporation of lake- level values up to 5 days lag in input vector to the used models (Fig. 3). Considering the correlation analyses and multi linear regression (MLR) model was used to evaluate the degree of effect of each variable and to select the most effective input vectors. The following combinations of input data were evaluated: (i) L_{t-1}, (ii) L_{t-3}, L_{t-2}, and L_{t-1} (iii) L_{t-5}, L_{t-4}, L_{t-3}, L_{t-2}, and L_{t-1}. In all cases, the output layer has only one neuron, the reservoir level L_t for the current day.

3.1 Prediction of reservoir level fluctuations of the Millers Dam

It is clear from Table 1 that the data show high skewness coefficient; that is far to normal distribution. The difference in statistical properties of the training, and testing data is infinitesimal and can be considered insignificant. Nevertheless, according to the partial autocorrelation function, the 5 lag times have

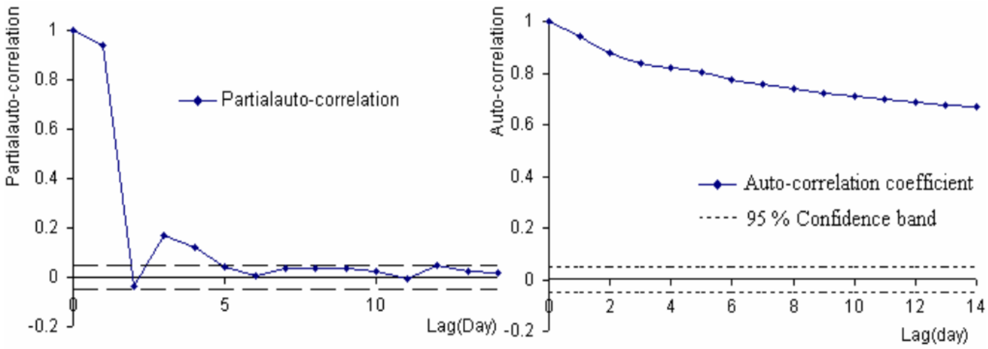

Fig. 3. Autocorrelation and partial autocorrelation functions of daily reservoir levels

significant influence on predicting level for the following time step (L_{t-1}), so it seems that up to 5 reservoir levels are necessary for task on hands. MSE and MAE values of MLR model for various lead times during the test period are shown in Table 2. Using L_{t-1} as the only input variable resulted in less accurate simulations with MSE = 0.0068 m and MAE = 0.0602 m, while the input combination L_{t-5}, L_{t-3}, and L_{t-1} gives the best results with MSE = 0.0060 m and MAE = 0.0567 m compared to others. Thus, the MLR application indicates that introducing reservoir water levels up to L_{t-5} significantly increases the modeling accuracy, while adding more variables does not noticeably affect the prediction accuracy.

The backpropagation neural network described in the preceding section was implemented in MATLAB code for predicting reservoir levels using the previously recorded daily reservoir level values. In all MLP models, simulations during the training and testing stages, after trying various MLP structure, a network structure is taken with one hidden layer having different nodes and one output neuron. The number of hidden layer nodes of each ANN model has been determined iteratively. Different number of input combinations is performed for real observed data sets to find out how well the models perform. The ANN network's training was stopped after 1000 epochs. The testing statistics of ANN models in term of R, MAE and MSE are also presented in Table 2.

The ANN model whose inputs are the current reservoir level as well as five previous reservoir levels (five-input ANNs) produces the best results among other input combinations.

Table 2 represents the ANN, ARMA, AR and MLR results of daily dam reservoir level forecasts with various input combination for the testing periods. In the present study, each input combination was applied for introducing the models to produce good predictions. The table clearly shows that the ANN model using Bayesian regularization technique while the input combination L_{t_5}, L_{t_3}, and L_{t_1} (as shown ANN5 on the table) gives the best results.

Fig. 4 displays the observed and simulated reservoir level values for L_{t-1} input combination produced by the optimal ANN, ARMA, AR and MLR models during the testing period. ANN model performs better than the other models in terms of the R, MSE and MAE statistics, in the test period. Fig. 4 shows that the ANN1 model has less scattered predictions than the other models and provided the highest R coefficient (0.887) for the L_{t-1} input combination. The overall evaluation of the other three methods reveals that the ARMA, AR and MLR models give similar accuracy. The similar accuracy of the ARMA and AR models can be clearly seen from the Fig. 4 and Table 2.

Having selected the optimal input combination ANN3, the ARMA, AR, ANN and MLR models were applied to forecast dam reservoir levels (see Table 2). Fig. 5 displays the observed and simulated reservoir level values for L_{t-3}, L_{t-2} and L_{t-1}input combination produced by the optimal ARMA, AR, ANN and MLR models during the test periods. The overall evaluation of the all methods reveals that ANN model performs better than the other models. The test results also indicate that increasing input combination leads to little increase in the model accuracy. The R increases from 0.887 to 0.893 for the ANN, from 0.792 to 0.800 for the other models (Fig. 5).

AR and ARMA models are experimented in this study and the application of the AR(3) and ARMA(5,5) models provided similar low R coefficient (0.792-0.799) for the test period. The model predictions for the test period are compared with the observed reservoir levels in the scatter plots. Such scatter graphs are given for AR(1), AR(1), AR(3), ARMA(1,1), ARMA(3,3) and ARMA(5,5) models in Figs. 4, 5 and 6, respectively. It can be seen from these scatter plots of autoregressive models provide a low agreement between observation and prediction reservoir levels. However, AR and ARMA models has the smallest R coefficient (0.792-0.799) compared to ANN and MLR results of the second and third input combination.

The predictions of different input combinations for 1-day ahead show that the model accuracy increases with different input combinations. Fig. 6 provides the scatter plots of the observed and simulated dam reservoir levels during the ANN5 test periods. As seen from Table 2, ANN5 model has the smallest MSE (0.0032 m), MAE (0.0415 m) and the highest R (0.893) for five-input combination during the test period. According to the entire model results, ANN singles out as having very small MSE, MAE and high R values for the same input combination.

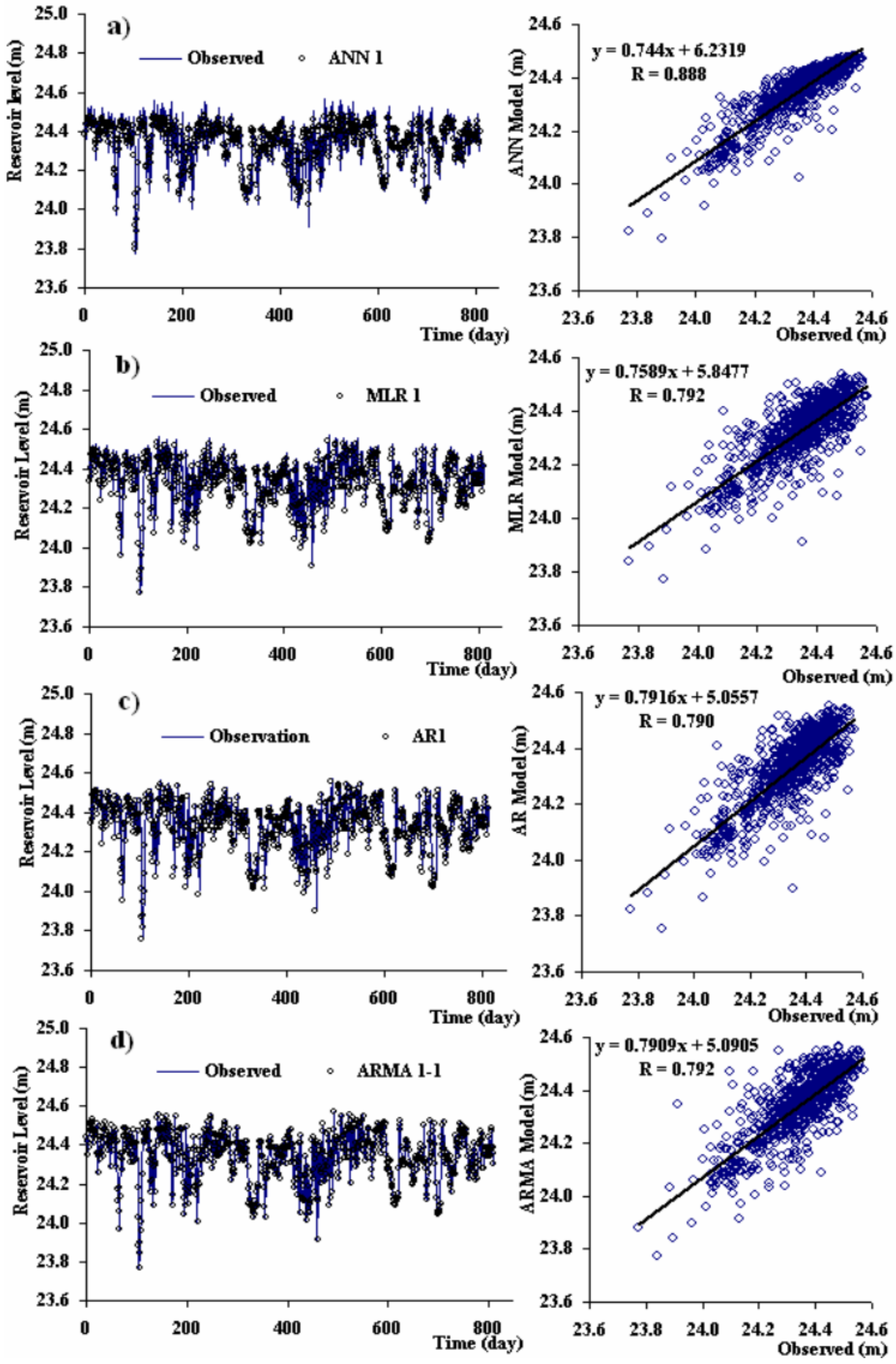

Fig. 4. Observed and predicted reservoir levels for Millers Dam in the test period a) ANN1, b) MLR1 , c) AR(1) and d) ARMA(1,1)

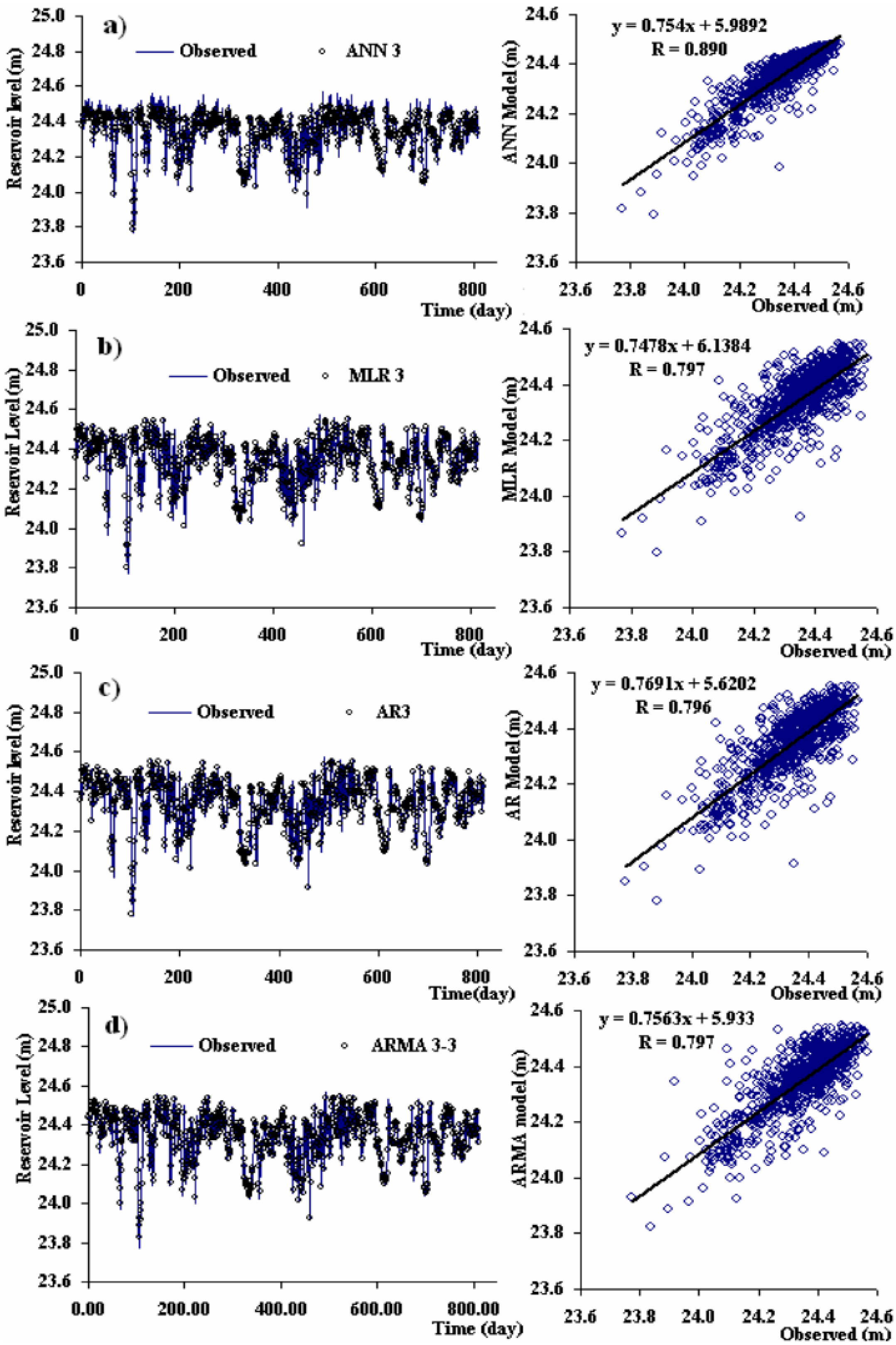

Fig. 5. Observed and predicted reservoir levels for Millers Dam in the test period a) ANN3, b) MLR3 , c) AR3 and d) ARMA(3,3)

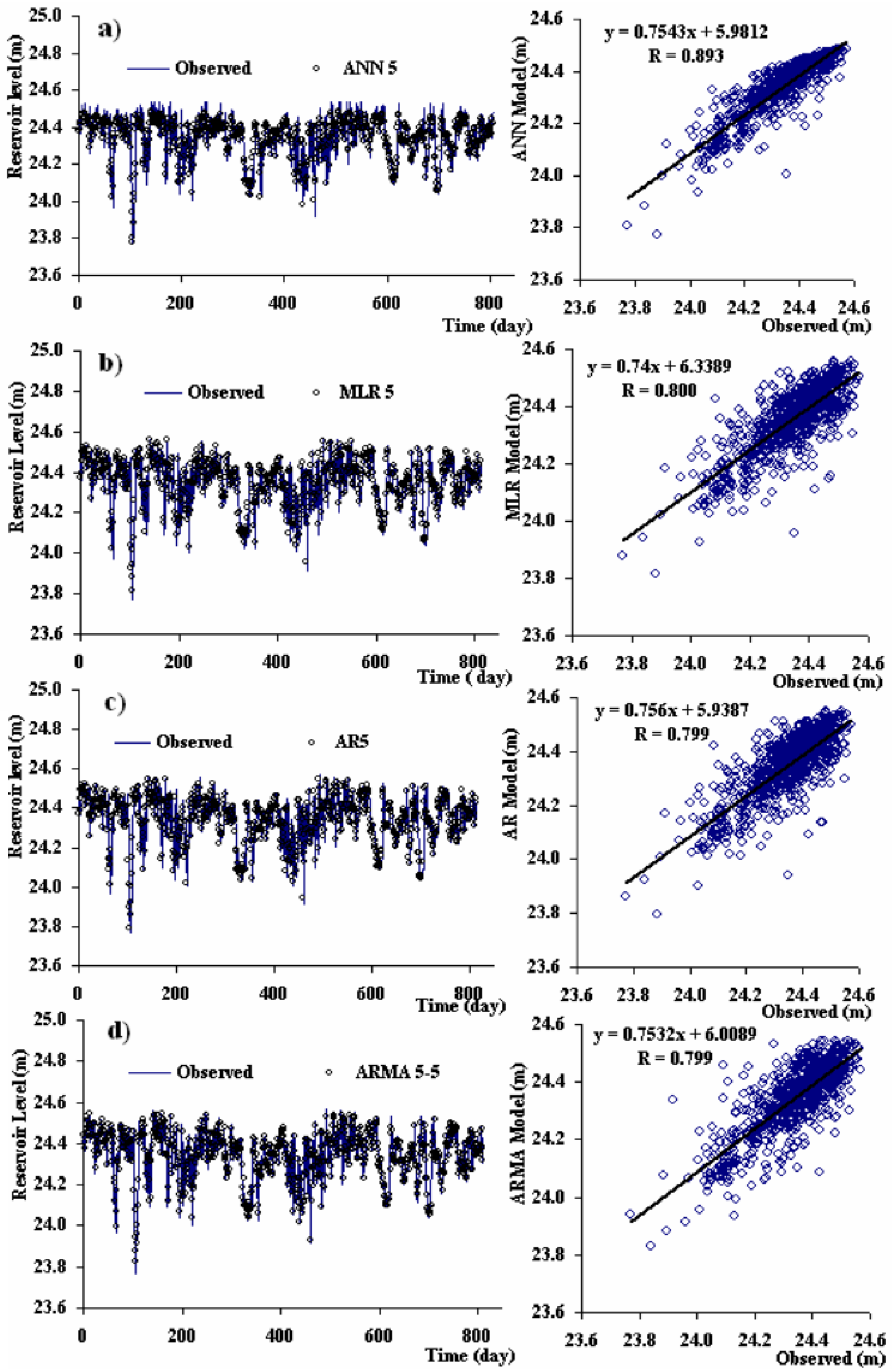

Fig. 6. Observed and predicted reservoir levels for Millers Dam in the test period a) ANN5, b) MLR5 , c) AR(5) and d) ARMA(5,5)

Tab. 2. Comparison of different models with MSE, MAE and R for testing period

Models	Input combination	MSE (m)	MAE (m)	*R*
ANN1	L_{t-1}	0.0034	0.0425	0.887
ANN3	L_{t-3}, L_{t-2}, and L_{t-1}	0.0033	0.0418	0.891
ANN5	L_{t-5}, L_{t-4}, L_{t-3}, L_{t-2}, and L_{t-1}	0.0032	0.0415	**0.893**
MLR1	L_{t-1}	0.0068	0.0602	0.792
MLR3	L_{t-3}, L_{t-2}, and L_{t-1}	0.0061	0.0564	0.797
MLR5	L_{t-5}, L_{t-4}, L_{t-3}, L_{t-2}, and L_{t-1}	0.0060	0.0567	**0.800**
AR(1)	L_{t-1}	0.0069	0.0602	0.792
AR((1))	L_{t-3}, L_{t-2}, and L_{t-1}	0.0063	0.0573	0.796
AR((3))	L_{t-5}, L_{t-4}, L_{t-3}, L_{t-2}, and L_{t-1}	0.0060	0.0564	**0.799**
ARMA(1-1)	L_{t-1}	0.0066	0.0587	0.792
ARMA(3-3)	L_{t-3}, L_{t-2}, and L_{t-1}	0.0061	0.0565	0.798
ARMA(5-5)	L_{t-5}, L_{t-4}, L_{t-3}, L_{t-2}, and L_{t-1}	0.0060	0.0566	**0.799**

4 Conclusions

Predicting dam reservoir level fluctuations is of importance for planning and constructing lake coastal structures and other industrial operations as well as water resources integrated management. In the present study, dam reservoir level observations from the Millers Ferry Dam in USA were forecasted by using ANN, MLR, AR, and ARMA models. The following points can be drawn from the study.

The presented ANN model provides better estimates of the reservoir level fluctuations than the conventional models.

The multi-linear regression model did not reach the desired accuracy in the problem and it can not provide a good prediction for reservoir levels.

Autoregressive and autoregressive moving average models provide more scattered results compared with the ANNs for all input combination. It is possible to state that a neural network solution can provide a tighter fit to the observed data.

The ANN correctly adapts to the changing input conditions, such as water demand policy changes in the reservoir operation. The advantages of the ANNs over conventional methods in the prediction of reservoir levels can be explained by saying that ANN structure includes the non-linear dynamics of the problem in the whole data set.

The results presented here showed the capability of the applied models for learning the nonlinear behavior of reservoir level variations in terms of R, MSE, and MAE.

When an ANN model is developed for a specific region, the model can be quite helpful in the water resources management studies. The monthly reservoir level estimations can be quite informative for the determination of the periodic water supply strategies, the hydroelectric energy computations and the flood management studies. Finally, these results show that ANN is a useful alternative method for dam reservoir level prediction.

ANN method was used in this study for predicting dam reservoir level fluctuations. Some other nonlinear methods such as fuzzy logic, genetic programming etc can also be used and compared with ARMA and MLR methods in the future studies.

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