An artificial neural network model for river flow forecasting a comparison between ANN and ARIMA

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Abstract—Careful modeling and precise river flow forecast is fundamental and is the basis for a wide range of problems related to the management of river hydrologic systems. Artificial Neural Networks (ANNs) are being used increasingly to predict and forecast water resources variables specially MLP network. The Feed forward Multi-layer perceptron (MLP) with back propagation algorithm has applied in this research. The selected ANN model were used to train and forecast the daily flows into the Silveh Dam on the Lavin River in IRAN, between years 2002–2012. In order to compare the performance of MLP, Box-Jenkins model was used. The results indicated that, in general, ANN approaches yielded reasonably good forecasts for 7-day lead times in comparison with the Auto Regressive Integrated Moving Average (ARIMA) model.

Keywords; River flow forecasting; ARIMA; ANN; Feed forward multi-layer perceptron (MLP)

1. Introduction
Careful modeling and precise river flow forecast is fundamental and is the basis for a wide range of problems related to the management of river hydrologic systems; on the other hand it is important for the livelihoods of inhabitants located near river [1]. Thus accurate time series forecasting has received attention of tremendous number of researchers and motivated them to develop innovative models. As the earliest methods the hydrological models especially rainfall-runoff models was greatly used [2]. Since the great use of rainfall-runoff models, Traditional methods of time series forecasting have been widely used by researchers. Among all the methods, Box and Jenkins 1976 models, especially Auto Regressive Integrated Moving Average (ARIMA) have been applied most However; these models suffer from assumption of linearity [2]. Considering the nonlinear pattern of hydrologic time series, nonlinear models have been proposed as alternative techniques. Over past years, Artificial Neural Networks (ANNs) were introduced as an efficient tool in hydrology forecasting. There are a number of studies in which neural networks are used to address water resources problems[3]. The structure of the paper is as follows: Section 2 gives a brief description of the recent and available literature. A brief review of ANN modeling methods is presented in Section 3. Section 4 provides a brief description of the study area and data used. A number of discussions and conclusions of the study are given in Sections 5 and 6, respectively.

Classical techniques
Classical techniques can be classified into two main groups. Hydrological and traditional black-box approaches. [2], have provided detailed information on classification of hydrological models and their characteristics. Although, the Hydrological (physically-based) models are very useful to understand river flow mechanisms, they also possess a great number of difficulties. In the traditional black box approaches the class of auto regressive integrated moving average proposed by Box and Jenkins (1976), have been greatly employed [1]. [4] have applied ARMA and ARIMA models to forecast monthly inflow into the DEZ dam reservoir in Iran. Their results determined that ARIMA model can forecast inflow with lower error than the ARMA model.

Recent methods, Artificial Intelligence (AI) techniques
Application of conventional or statistical techniques is not adequate enough in order to understand and model highly non-linear hydrological behaviors. Therefore, there is a great need for improvement of mathematical modeling. Artificial Intelligence (AI) models have been received great attention over the last 20 years. AI offers flexible and non-parametric algorithm capable of identifying the complex non-
linear relationships between inputs and outputs datasets \[2\]. A significant number of studies have confirmed the usefulness of ANN models in river flow forecasting. Among these models, the Multi-Layer Perceptron (MLP) model optimized with a back propagation (BP) algorithm is identified as the most popular ANN techniques \[6\].

\[7\] implemented two types of ANN models including multi-layer perceptron network (MLP) and a radial basis function network (RBF). The performances of these networks were compared with a conceptual rainfall-runoff model. Based on their findings, these models were found to be slightly better than traditional hydrologic model for river flow forecasting. Moreover, Back Propagation Network (BPN) shows slightly better performance both in the training and verification periods than the RBF network. Regarding to the literature review, among these combinations of ANNs, the multi-layer feed forward networks, also known as multi-layer perceptron (MLPs), trained with a back-propagation learning algorithm have been (also called Back Propagation Network, BPN) found to provide the best performance with regard to input–output function approximation, such as forecasting \[1, 6\]

2. Experimental

**ARIMA Modeling approach**

For more than half a century, ARIMA models have dominated many areas of time series forecasting. In an ARMA (p,q) model, the future value of a variable is assumed to be a linear function of several past observations and random errors, which is mentioned below (1).

\[ Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + \theta_q a_{t-q} \]  

Where p and q are model orders, \( \phi \) and \( \theta \) are model parameters and \( a_t \) are observations. Random errors, \( a_t \), are assumed to be independently and identically distributed with a mean of zero and a constant variance of \( \sigma^2 \).

The ARIMA (p,d,q) formulation is also mentioned (2).

\[ \phi(B) \nabla^d Z_t = \theta(B) a_t \]  

Where \( d \) is the number of regular differencing. The Box-Jenkins methodology includes three iterative steps of model identification, parameter estimation, and diagnostic checking. Box and Jenkins proposed to use the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the sample data as the basic tools to identify the order of the ARMA model. Some other order selection methods have been proposed based on validity criteria, the information-theoretic approaches such as the Akaike’s information criterion (AIC). Model identification, parameter estimation is done by Eviews 7.1 software using AIC.

**Artificial Neural Networks (ANNs) and Multi-layer Perceptrons (MLP) Network**

Artificial neural networks are flexible mathematical structures. ‘Training’ and ‘learning’ makes ANN capable of describing complex non-linear problems. A neural network consists of a large number of simple processing elements that are variously called neurons, units, cells, or nodes; each neuron is connected to other neurons by means of direct communication links, each with an associated weight and the activation function \[8, 9\]. The network usually has two or more layers of processing units where each processing unit in each layer is connected to all processing units in the adjacent layers. Multi-layer perceptrons are feed-forward networks with one or more hidden layers. The most common learning rule for multi-layer perceptrons is the back propagation algorithm. A neural network with such type of learning algorithms is usually referred to as BPN. The first layer connects with the input variables and is called the input layer. The last layer connects to the output variables and is called the output layer. The layer in between the input and output layers is called the hidden layer. The effective incoming signal \( (s_i) \) to node \( j \) is the weighted sum of all the incoming signals \( (3) \).
The effective incoming signal, $S_j$, is passed through a non-linear activation function (sometimes called a transfer function or threshold function) to produce the outgoing signal ($y_j$) of the node. The most commonly used function in an MLP trained with back-propagation algorithm is the sigmoid function. The sigmoid function that is mostly used for ANNs is the logistic function (4):

$$f(s_j) = \frac{1}{1 + e^{-s_j}}$$

In which $s_j$ can vary on the range $\pm \infty$, but $y_j$ is bounded between 0 and 1.

The data has been collected for the Silveh Dam which is located on the Lavin River in south western of Orumiyeh, Iran. The river basin ranges between 36°, 30' to 36°, 53' North latitude and 45°, 05' to 45°, 38' East longitude (Fig. 1). The primary objectives of Silveh Dam briefly include: (i) To provide water for irrigation of about 28156 hectares of lands, (ii) To provide drinking water for the people living in the town of Piranshahr and (iii) To provide water for environmental protection of Lake Urmia. Data used in this research include daily records of river flow volume (m3/s) between 2002 and 2012 that have been received from the Silveh Hydrometric Station located at the North Part of Silveh Dam. A total number of 3650 data between a period of September 2002 and September 2012 was used. In order to validate the proposed approach, we have utilized 70% of the available data to train the models, 15% to estimate the best configuration parameters and the remaining 15% of data for testing purposes.

3. Results and Discussion

The purpose of this study is to predict inflow ($Y_t$) at the time ($t$). In order to predict the inflow at time ($t$), inflow values up to a lag time of 7 days was used. Therefore, the input layer of network will consist of inflow values up to a lag period of 7 days (i.e. $Y_{t-1}$, $Y_{t-2}$, $Y_{t-3}$, $Y_{t-4}$, $Y_{t-5}$, $Y_{t-6}$ and $Y_{t-7}$ values) and output layer will consist of the inflow values $Y_t$. For comparison reasons ANN is compared with ARIMA Times series Model. Using the Eviews package software, the best-fitted model for Box and Jenkins approach, which has the minimum AIC=15.03 is ARIMA (3,0,3). Matlab Neural Network Toolbox is used to construct different one and two hidden-layer MLP networks with a range of 3–21 hidden neurons in the hidden layer. The model results with different architectures indicate that 3-node networks generally perform best. Therefore, the chosen configuration for MLP–ANNs is 7–2–1, namely, seven inputs, two hidden layer with three hidden neurons and one output. In order to provide an indication of goodness of fit between the observed and forecasted values the root mean squared error (RMSE) and mean absolute error (MAE) values were considered. The results indicate that RMSE and MAE as the performance measures are minimum (0.05739, 0.04008) for 7-2-1 (with 7 inputs, 2 hidden layer and 1 output layer) ANN architecture (Table 1).

![Image 1: Silveh Dam and Lavin River](image1.png)

**Table 1: The MLP results**

<table>
<thead>
<tr>
<th></th>
<th>MAE</th>
<th>RMSE</th>
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<tbody>
<tr>
<td>MLP(7–2–1)</td>
<td>0.05062</td>
<td>0.06074</td>
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</table>

To assess the performance of ANN in River flow forecasting, we compare the MLP ANN with famous and regular Time Series Model, Auto Regressive Integrated Moving average Model. According to the RMSE and MAE values, the possibility of using artificial neural networks for river flow forecasting instead of ARIMA models is demonstrated in Table 2. The MAE has increased significantly in performance from 19.48193 to 0.04008. The RMSE has also changed from 23.56372 to 0.05739. The results show that ANN performs much better than ARIMA model. The selected network was then used to forecast 33 ahead inflows; Figure 2 shows the predicted data versus observed data. The MAE and RMSE in this step are 0.05062 and 0.06074 which is shown in table 2.

![Image 2: predicted data versus observed data](image2.png)

**Table 2: Comparison of ANN and ARIMA model**

<table>
<thead>
<tr>
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<th>MLP(7–2–1)</th>
<th>ARIMA(3,0,3)</th>
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<tbody>
<tr>
<td>MAE</td>
<td>RMSE</td>
<td>MAE</td>
</tr>
<tr>
<td>Test</td>
<td>0.05062</td>
<td>0.06074</td>
</tr>
</tbody>
</table>
4. Conclusions
The purpose of the research was to seek whether neural network models can be used to predict daily flow of the Lavin River in northwest Iran. We found that neural networks produced fairly accurate results. The other goal of the research was to compare between different methods to understand whether artificial neural networks can be used for flow forecasts instead of other black box and hydrological models. The real data indicate the excellent performance of MLP-ANN for forecasting daily inflow of Silveh dam. Results show that MLP possesses efficiency, effectiveness, and robustness. Furthermore, the forecasting performance values MAE and RMSE, reveals again the excellent effectiveness of the proposed MLP. The predictions from MLP model were compared with those obtained from ARIMA traditional time series approach. Owing to its ability in recognizing time series patterns and nonlinear characteristics, the accuracy measures RMSE, MAE demonstrated that the proposed model provided much better accuracy over ARIMA method for inflow forecasting. Therefore, the proposed model can be used for the Lavin River and other hydro meteorologically similar rivers for predicting daily inflow.

5. References