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Daily River Flow Forecasting Using Artificial Neural Networks and Auto-Regressive Models

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Abstract

Estimating the flows of rivers can have a significant economic impact, as this can help in agricultural water management and in providing protection from water shortages and possible flood damage. This paper provides forecasting benchmarks for river flow prediction in the form of a numerical and graphical comparison between neural networks and auto-regressive (AR) models. Benchmarking was based on 7 and 4-year periods of continuous river flow data for 2 rivers in the USA, the Blackwater River and the Gila River, and a 2-year period of streamflow data for the Filyos Stream in Turkey. The choice of appropriate artificial neural network (ANN) architectures for hydrological forecasting, in terms of hidden layers and nodes, was investigated. Three simple neural network (NN) architectures were then selected for comparison with the AR model forecasts. Sum of square errors (SSEs) and correlation statistic measures were used to evaluate the models' performances. The benchmark results showed that NNs were able to produce better results than AR models when given the same data inputs.

Key words: Streamflow forecasting, Neural networks, Auto-regressive models.

Introduction

Many of the activities associated with the planning and operation of the components of a water resource system require forecasts of future events. For the hydrologic component, there is a need for both short term and long term forecasts of streamflow events in order to optimize the system or to plan for future expansion or reduction. Many of these systems are large in spatial extent and have a hydrometric data collection network that is very sparse. These conditions can result in considerable uncertainty in the hydrologic information that is available. Furthermore, the inherently non-linear relationships between input and output variables complicate attempts to forecast streamflow events. There is thus a need for improvement in forecasting techniques. Many of the techniques currently used in modeling hydrological time series and generating synthetic streamflows assume linear relationships amongst the variables. The 2 main groups of techniques include physically based conceptual models and time series models. Techniques in the former group are specifically designed to mathematically simulate the subprocesses and physical mechanisms that govern the hydrological cycle. These models usually incorporate simplified forms of physical laws and are generally nonlinear, time-invariant, and deterministic, with parameters that are representative of watershed characteristics (Hsu *et al.*, 1995) but ignore the spatially distributed, time-varying, and stochastic properties of the rainfall–runoff (R–R) process. Kitanidis and Bras (1980 a,b) state that conceptual watershed models are reliable in forecasting the most important features of the hydrograph. However, the implementation and calibration of such a model can typically present various difficulties (Duan *et al.*, 1992), requiring sophisticated mathematical tools (Sorooshian *et al.*, 1993), significant amounts of calibration data (Yapo *et al.*, 1996), and some degree of expertise and experience with the model (Hsu *et al.*, 1995). The problem with conceptual models is that empirical regularities or periodicities are not always evident and can often be masked by noise.

In time-series analysis, stochastic models are fitted to one or more of the time-series describing the system for purposes that include forecasting, generating synthetic sequences for use in simulation studies, and investigating and modeling the underlying characteristics of the system under study. Most of the time-series modeling procedures fall within the framework of multivariate autoregressive moving average (ARMA) models (Raman and Sunilkumar, 1995).

ANNs have been successfully applied in a number of diverse fields, including water resources. In the hydrological forecasting context, recent experiments have reported that ANNs may offer a promising alternative for R-R modeling (Smith and Eli, 1995; Shamseldin, 1997; Tokar and Johnson, 1999), streamflow prediction (Zealand *et al.*, 1999; Chang and Chen, 2001; Sivakumar *et al.*, 2002; Kisi, 2004; Cigizoglu and Kisi (in press)) and reservoir inflow forecasting (Saad *et al.*, 1996; Jain *et al.*, 1999). Recently, Coulibaly *et al.* (1999) reviewed the ANN-based modeling in hydrology over the last years, and reported that about 90% of experiments make extensive use of the multi-layer feed-forward neural networks (FNN) trained by the standard backpropagation (BP) algorithm (Rumelhart *et al.*, 1986).

The main purposes of this paper are to analyze and to discuss stochastic modeling of time series using FNN and traditional modeling techniques. There are many parameters (precipitation, evapotranspiration, ground water, initial moisture content of soil etc.) that affect the next day runoff. Although it is possible to identify sophisticated models taking into consideration the hydrological and hydro-meteorological variables such as precipitation, runoff, temperature and evaporation, it is economically preferable that a model that simulates the flow variations on the basis of past discharge records be available to the decision maker, whether administrator, local authority or technical operator. Therefore, only the past discharge records were used as inputs in the present study. The FNN and AR models are applied to forecast daily river flow for 3 rivers, the Blackwater River and Gila River in USA and the Filyos Stream in Turkey. The results are compared and conclusions are presented.

Artificial Neural Networks

General

The human brain contains billions of interconnected neurons. Due to the structure in which the neurons are arranged and operate, humans are able to quickly recognize patterns and process data. An ANN is a simplified mathematical representation of this biological neural network. It has the ability to learn from examples, recognize a pattern in the data, adapt solutions over time, and process information rapidly. The application of ANNs to water resources problems is rapidly gaining popularity due to their immense power and potential in the mapping of nonlinear system data.

A water resources system may be nonlinear and multivariate, and the variables involved may have complex interrelationships. Such problems can be efficiently solved using ANNs. The processes that involve several parameters are easily amenable to neurocomputing. Among the many ANN structures that have been studied, the most widely used network structure in the area of hydrology is the multilayer, feed-forward network. The remaining discussion is focused on such networks.

An ANN consists of a number of data processing elements called neurons or nodes, which are grouped in layers. The input layer neurons receive the input vector and transmit the values to the next layer of processing elements across connections. This process is continued until the output layer is reached. This type of network in which data flows in one direction (forward) is known as a feed-forward network. The ANN theory has been described in many books, including the text by Rumelhart et al. (1986). The application of ANNs has been the subject of a large number of papers that have appeared in the recent literature. Therefore, to avoid duplication, this section will be limited to main concepts.

A 3-layer, feed-forward ANN is shown in Figure 1. It has input, output, and hidden middle layers. Each neuron in a layer is connected to all the neurons of the next layer, and the neurons in one layer are not connected among themselves. All the nodes within a layer act synchronously. The data passing through the connections from one neuron to another are multiplied by weights that control the strength of a passing signal. When these weights are modified, the data transferred through the network changes; consequently, the network output also changes. The signal emanating from the output node(s) is the network's solution to the input problem.

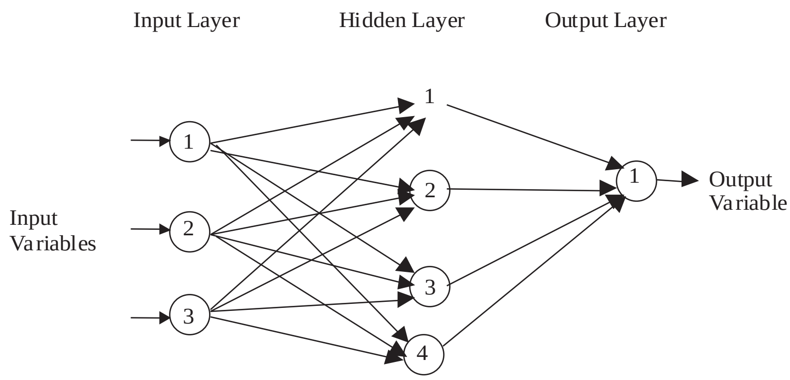

Figure 1. A 3-layer ANN architecture used for flow estimation.

Each neuron multiplies every input by its interconnection weight, sums the product, and then passes the sum through a transfer function to produce its result. This transfer function is usually a steadily increasing S-shaped curve, called a sigmoid function. The sigmoid function is continuous, differentiable everywhere, and monotonically increasing. The output y_j is always bounded between 0 and 1, and the input to the function can vary $\pm\infty$. Under this threshold function, the output y_j from the j_{th} neuron in a layer is

$$y_j = f\left(\sum w_{ji}x_i\right) = \frac{1}{1+e^{-\left(\sum w_{ji}x_i\right)}} \qquad (1)$$

where w_{ji} = weight of the connection joining the j_{th} neuron in a layer with the i_{th} neuron in the previous layer, and x_i = value of the i_{th} neuron in the previous layer.

Training of ANNs

The process of determining ANN weights is called learning or training and is similar to the calibration of a mathematical model. The ANNs are trained with a training set of input and known output data. At the beginning of training, the weights are initialized, either with a set of random values or based on some previous experience. Next, the weights are systematically changed by the learning algorithm such that for a given input the difference between the ANN output and actual output is small. Many learning examples are repeatedly presented to the network, and the process is terminated when this difference is less than a specified value. At this stage, the ANN is considered trained.

The backpropagation algorithm based upon the generalized delta rule proposed by Rumelhart *et al.* (1986) was used to train the ANN in this study. In the back-propagation algorithm, a set of inputs and outputs is selected from the training set and the network calculates the output based on the inputs. This output is subtracted from the actual output to find the output-layer error. The error is backpropagated through the network, and the weights are suitably adjusted. This process continues for the number of prescribed sweeps or until a prespecified error tolerance is reached. The mean square error over the training samples is the typical objective function to be minimized.

After training is complete, the ANN performance is validated. Depending on the outcome, either the ANN has to be retrained or it can be implemented for its intended use. An ANN is better trained as more input data are used. The number of input, output, and hidden layer nodes depend upon the problem being studied. If the number of nodes in the hidden layer is small, the network may not have sufficient degrees of freedom to learn the process correctly. If the number is too high, the training will take a long time and the network may sometimes overfit the data (Karunanithi *et al.*, 1994).

AR models

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

$$X_t = \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + Z_t \qquad (2)$$

where Z_t is a purely random process and $E(Z_t) = 0$, $Var(Z_t) = \sigma_Z^2$. The parameters $\alpha_1, \ldots \alpha_p$ are called the AR coefficients. The name "auto-regressive" comes from the fact that X_t is regressed on the past values of itself.

In this study, standard AR models were fitted to the river flow data. The least squares method was used to estimate AR coefficients. The maximum entropy method (MEM, or Burg algorithm) is an alternative way to estimate AR coefficients. The model that gives the maximum correlation and the minimum sum of square errors (SSE) was selected. The AR(5) and AR(2) were found appropriate for the Blackwater. For the Gila River and Filyos Stream, however, the AR(2) model gave the best results.

Case study

The flow data of the 2 stations operated by the U.S. Geological Survey (USGS) and the data of the Derecikviran Station operated by the Turkish General Directorate of Electrical Power Resources Survey and Development Administration (EIE) were used in the study. The locations of these stations are illustrated in Figures 2 and 3. The 1^{st} station (USGS Station No: 02047500, datum of gauge is 9.45 m above sea level) is on the Blackwater River near Dendron in Virginia, the 2^{nd} station (USGS Station No: 09442000, datum of gauge is 1017 m above sea level) is on the Gila River near Clifton in Arizona, the 3^{rd} station (EIE Station No: 1335, datum of gauge is 1 m above sea level) is on the Filyos Stream in Turkey. The drainage areas at these sites are 761 km^2, 10386 km^2 and 133300 km^2, respectively.

For the 1^{st} station, the data for October 01 1990 to September 30 1996 (6 water years) were chosen for calibration, and data for October 01 1996 to September 30 1997 (1997 water year) were chosen for validation, arbitrarily. For the 2^{nd} station, the data for October 01 1995 to September 30 1998 (3 water years) were used for calibration, and data for October 01 1998 to September 30 1999 (1999 water year)

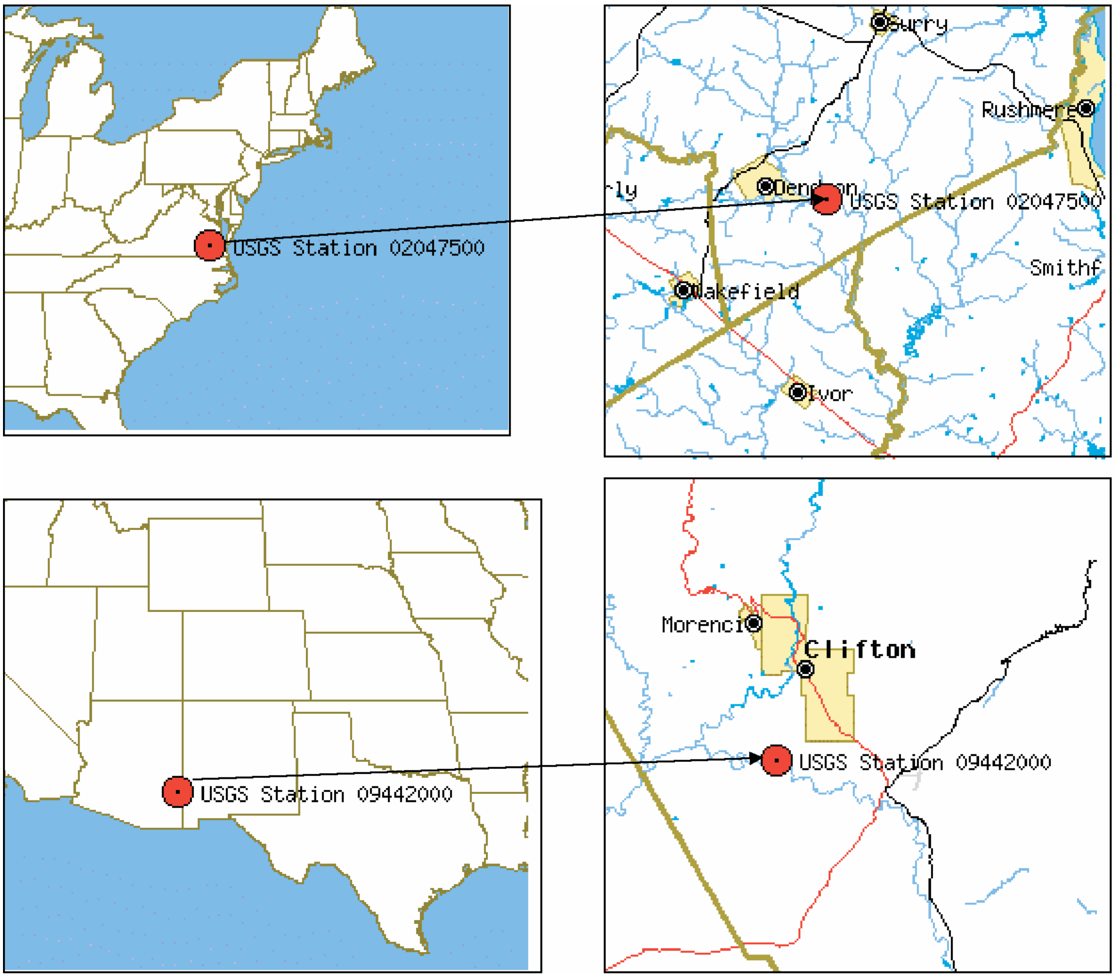

Figure 2. The locations of the stations operated by the USGS.

were chosen for validation. For the 3^{rd} station, the data for October 01 1999 to September 30 2000 were chosen for calibration, and data for October 01 2000 to September 30 2001 were used for validation It may be noted that the periods from which calibration and validation data were chosen span the same temporal seasons (October–September).

The coefficients of correlation between 2 variables, say x and y, whose n pairs are available, can be calculated by

$$corr = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3}$$

where the bar denotes the mean of the variable. The auto-correlation coefficients of the flow data of each river for the calibration and validation period are given in Table 1. The correlations of the Gila River are not as high as those of the other rivers. From 1 to 6 antecedent flow values were taken into consideration as input vectors of the ANN and AR models.

Application and Results

In general, the architecture of a multi-layer FNN can have many layers where a layer represents a set of parallel processing units (or nodes). The 3-layer FNN (Figure 1) used in this study contains only 1 intermediate (hidden) layer. Multi-layer FNNs can have more than 1 hidden layer, although theoretical studies have shown that a single hidden layer is sufficient for ANNs to approximate any complex non-linear function (Cybenko, 1989; Hornik *et al.*, 1989). Indeed, many experimental results seem to confirm that 1 hidden layer may be enough for most forecasting problems (Zhang *et al.*, 1998; Coulibaly *et al.*, 1999). Therefore, in this study, 1 hidden layer FNN is used.

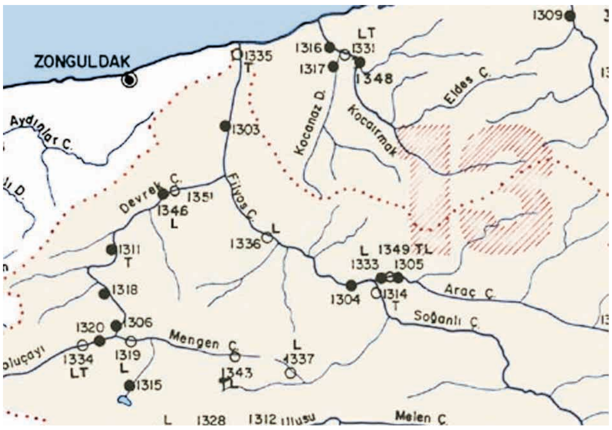

Figure 3. The location of the Derecikviran Station operated by the EIE.

Table 1. Auto-correlation coefficients for flow data of each river.

The Blackwater River							
		Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-5}	Q_{t-6}
Calibration period	Q_t	0.960	0.879	0.793	0.707	0.628	0.564
Validation period	Q_t	0.960	0.872	0.768	0.657	0.553	0.468
The Gila River							
		Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-5}	Q_{t-6}
Calibration period	Q_t	0.793	0.506	0.357	0.289	0.245	0.212
Validation period	Q_t	0.885	0.719	0.541	0.434	0.393	0.365
The Filyos Stream							
		Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-5}	Q_{t-6}
Calibration period	Q_t	0.933	0.814	0.721	0.662	0.620	0.591
Validation period	Q_t	0.935	0.832	0.740	0.666	0.597	0.524

A difficult task with ANNs involves choosing parameters such as the number of hidden nodes, the learning rate, and the initial weights. There is no theory yet to determine how many hidden units are needed to approximate any given function. The network geometry is problem dependent. Here, we use the 3-layer FNN with 1 hidden layer (Figure 1) and the common trial and error method to select the number of hidden nodes. The logistic function (Eq. (1)) is used as the hidden nodes and the output node activation function.

Before applying the ANN, the input data were normalized to fall in range [0.1, 0.9]. The river flow Q was standardized by the following formula:

$$Q_s = (Q/1.24Q_{\max}) + 0.1 \qquad (4)$$

where Q_s = standardized flow, and Q_{max} = maximum of the flow values.

In the present study, the following combinations of input data of flow were evaluated:

1. Q_{t-1}
2. Q_{t-1} and Q_{t-2}
3. Q_{t-1}, Q_{t-2}, and Q_{t-3}
4. Q_{t-1}, Q_{t-2}, Q_{t-3}, and Q_{t-4}
5. Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, and Q_{t-5}
6. Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, Q_{t-5}, and Q_{t-6}

The output layer had 1 neuron for current flow Q_t. In the trials, the number of neurons in the hidden layer varied between 1 and 6. The configuration giving the minimum SSE and maximum correlation was selected for each of the combinations. Table 2 gives the correlation and SSE for each combination for the Blackwater River. The correlation coefficient and SSE for the AR models are also given in Table 2. It can be seen from Table 2 that the SSE for the ANNs is smaller than the statistical method for the calibration period. From Table 2, the ANN combination 5 and AR(5) are selected for graphical representation.

Figures 4 and 5 contain a plot of the observed and computed discharges (using the AR(5) and the ANN combination 5) of the Blackwater River for the 1997 water year validation period. The difference between the standard backpropagation ANN and AR model is not clear from these figures. Close examination of the figures shows that the ANN estimates show a better match with the observed data. The 3 largest values can be given as samples. The ANN predicted the flow peak 2380 as 2135 m^3/s, an underestimation of 10%, while the AR(5) model predicted it as 1914, an underestimation of 20%. The ANN predicted the flow peaks 2310 and 2370, as 2356 and 2482 m^3/s, an overestimation of 0.02% and 0.05%, while the AR(5) model predicted 2772 and 2566, an overestimation of 17% and 0.08%, respectively.

The results of the calibration and validation for the Gila River are given in Table 3. Here also the trend of the results is the same as that for the Blackwater River. From Table 3, the ANN combination

Table 2. SSE and coefficient of correlation for ANN and AR models-training and testing data of the Blackwater River.

ANN model inputs	Nodes in hidden layer	Training/Calibration Data River flow (m^3/s)		Test/Validation Data River flow (m^3/s)	
		Correlation	SSE	Correlation	SSE
Q_{t-1}	3	0.961	$0.1884.10^5$	0.961	$0.4405.10^4$
Q_{t-1}, Q_{t-2}	2	0.975	$0.1253.10^5$	0.980	$0.2407.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3}	4	0.980	$0.1048.10^5$	0.986	$0.1881.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}	4	0.980	$0.1022.10^5$	0.982	$0.2012.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3} Q_{t-4}, Q_{t-5}	6	0.981	$0.9860.10^4$	0.985	$0.1841.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3} Q_{t-4}, Q_{t-5}, Q_{t-6}	4	0.980	$0.1062.10^5$	0.986	$0.1897.10^4$
AR(1)		0.959	$0.1921.10^5$	0.960	$0.4378.10^4$
AR(2)		0.971	$0.1393.10^5$	0.976	$0.2715.10^4$
AR(3)		0.973	$0.1293.10^5$	0.977	$0.2585.10^4$
AR(4)		0.974	$0.1240.10^5$	0.978	$0.2485.10^4$
AR(5)		0.975	$0.1183.10^5$	0.979	$0.2343.10^4$
AR(6)		0.975	$0.1183.10^5$	0.979	$0.2349.10^4$

2 and AR(2) were selected for graphical representation. The variation of observed and computed discharges for the 1999 water year validation period is given in Figures 6 and 7. The difference between the 2 models is evident. The ANN estimates are, however, quite close to the observed variation except for 1 peak that has been underestimated by the ANN. The ANN predicted the maximum flow peak 2440 as 1659 m^3/s, an underestimation of 32%, while the AR(2) model predicted 1472, an underestimation of 40%. As seen from Figures 6-7, the number of underestimations by the AR model for the other values is also much more that of those by the ANN.

The forecasting performances of the AR and ANN models for the Filyos Stream are presented in Table 4. As seen from the table, the 3^{rd} combination has the lowest SSE and the highest correlation among the ANN models. Of the AR models, the AR(2) model exhibited the best performance. The variation in the observed and the ANN (3^{rd} combination) and AR(2) forecasts is illustrated in Figures 8 and 9, respectively. Both models' forecasts seem to be close to the corresponding observed values. The ANN predicted the maximum flow peak 495 as 498 m^3/s, with an overestimation of 0.5%, while the AR(2) model computed 502, an overestimation of 1.4%.

Table 3. SSE and coefficient of correlation for ANN and AR models-training and testing data of the Gila River.

ANN model inputs	Nodes in hidden layer	Training/Calibration Data River flow (m^3/s)		Test/Validation Data River flow (m^3/s)	
		Correlation	SSE	Correlation	SSE
Q_{t-1}	2	0.819	$0.6786.10^5$	0.873	$0.3189.10^4$
Q_{t-1}, Q_{t-2}	2	0.896	$0.4061.10^5$	0.907	$0.2393.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3}	4	0.874	$0.4836.10^5$	0.906	$0.2395.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}	5	0.896	$0.4069.10^5$	0.903	$0.2497.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3} Q_{t-4}, Q_{t-5}	5	0.896	$0.4087.10^5$	0.903	$0.2483.10^4$
Q_{t-1}, Q_{t-2}, Q_{t-3} Q_{t-4}, Q_{t-5}, Q_{t-6}	6	0.898	$0.3967.10^5$	0.903	$0.2504.10^4$
AR(1)		0.793	$0.7700.10^5$	0.885	$0.3088.10^4$
AR(2)		0.818	$0.6996.10^5$	0.896	$0.2966.10^4$
AR(3)		0.831	$0.6423.10^5$	0.879	$0.3193.10^4$
AR(4)		0.831	$0.6416.10^5$	0.876	$0.3248.10^4$
AR(5)		0.832	$0.6361.10^5$	0.873	$0.3292.10^4$
AR(6)		0.832	$0.6357.10^5$	0.874	$0.3277.10^4$

Table 4. SSE and coefficient of correlation for ANN and AR models-training and testing data of the Filyos Stream.

ANN model inputs	Nodes in hidden layer	Training/Calibration Data River flow (m^3/s)		Test/Validation Data River flow (m^3/s)	
		Correlation	SSE	Correlation	SSE
Q_{t-1}	1	0.939	$0.1065.10^7$	0.936	$0.1390.10^6$
Q_{t-1}, Q_{t-2}	4	0.965	$0.6210.\ 10^6$	0.938	$0.1505.10^6$
Q_{t-1}, Q_{t-2}, Q_{t-3}	3	0.963	$0.6480.\ 10^6$	0.949	$0.1206.10^6$
Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}	4	0.961	$0.6847.\ 10^6$	0.940	$0.1433.10^6$
Q_{t-1}, Q_{t-2}, Q_{t-3} Q_{t-4}, Q_{t-5}	3	0.963	$0.6545.\ 10^6$	0.939	$0.1541.10^6$
Q_{t-1}, Q_{t-2}, Q_{t-3} Q_{t-4}, Q_{t-5}, Q_{t-6}	3	0.964	$0.6419.10^6$	0.940	$0.1444.10^6$
AR(1)		0.935	$0.7502.10^7$	0.936	$0.1336.10^6$
AR(2)		0.948	$0.7681.10^6$	0.943	$0.1210.10^6$
AR(3)		0.957	$0.7756.10^6$	0.941	$0.1264.10^6$
AR(4)		0.957	$0.9422.10^6$	0.939	$0.1303.10^6$
AR(5)		0.958	$0.1160.10^6$	0.936	$0.1382.10^6$
AR(6)		0.958	$0.7472.10^6$	0.936	$0.1375.10^6$

Figures 10, 11 and 12 show the extent of the match between the measured and predicted daily river flow values by ANN and AR models in term of a scatter diagram. The R^2 performances of ANN models are slightly better than those of AR models.

The relative SSE difference between the 5^{th} ANN combination and the AR(5) model in the calibration period for the Blackwater River is 20% that between the 2^{nd} ANN combination and the AR(2) model in calibration period for the Gila River is 42% and that between the 3^{rd} ANN combination and the AR(2) model in the calibration period for the Filyos Stream is 16%. Since the linearity in the Blackwater River and the Filyos Stream is much higher than that in the flow data of the Gila River (see Table 1), the relative SSE difference between the 2 methods for these rivers is much lower than the value for the Gila River. In other words, the performances of the AR and ANN models are closer to each other for the 1^{st} and 3^{rd} rivers whose auto-correlations are quite high.

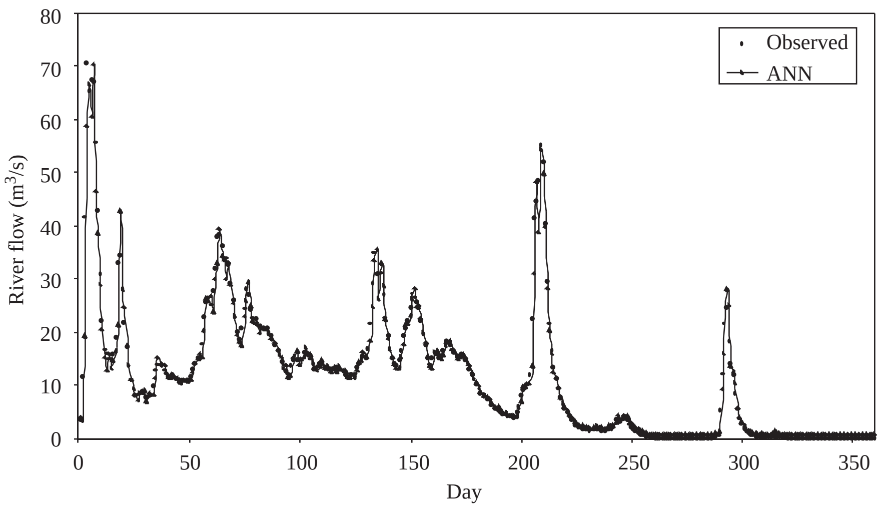

Figure 4. Observed and computed (ANN model) flows for the Blackwater River, validation period (01 October 1996-30 September 1997; 1997 water year).

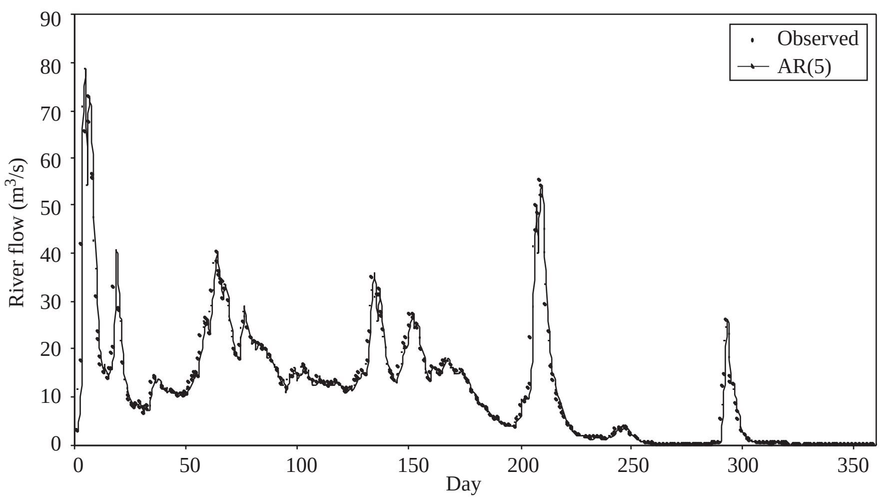

Figure 5. Observed and computed (AR model) flows for Blackwater River, validation period (01 October 1996-30 Sep 1997; 1997 water year).

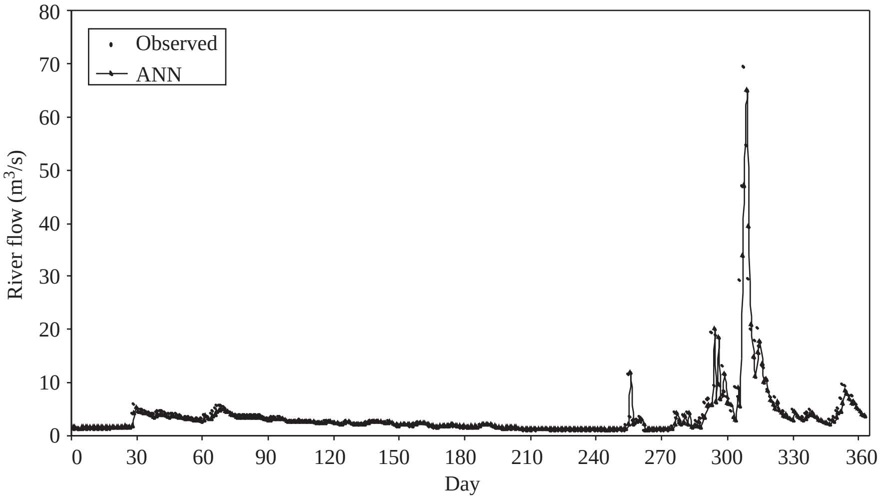

Figure 6. Observed and computed (ANN model) flows for the Gila River, validation period (01 October 1998-30 September 1999; 1999 water year).

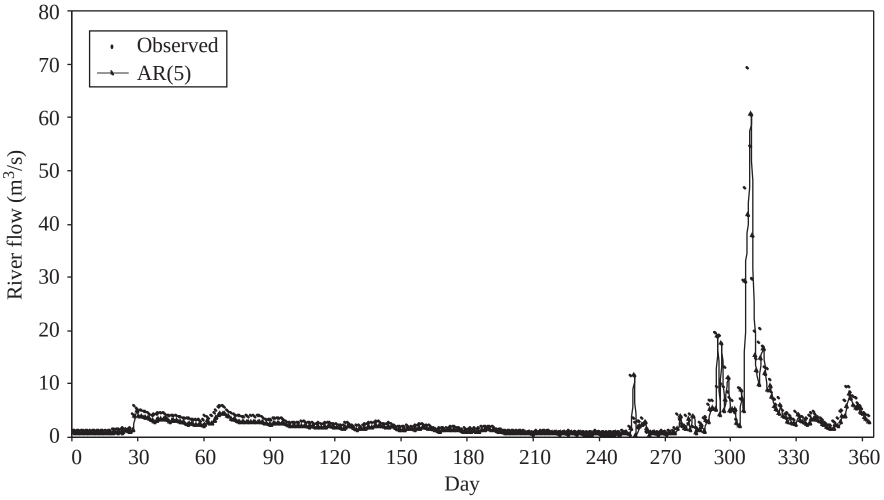

Figure 7. Observed and computed (AR model) flows for the Gila River, validation period (01.October1998-30.September1999; 1999 water year).

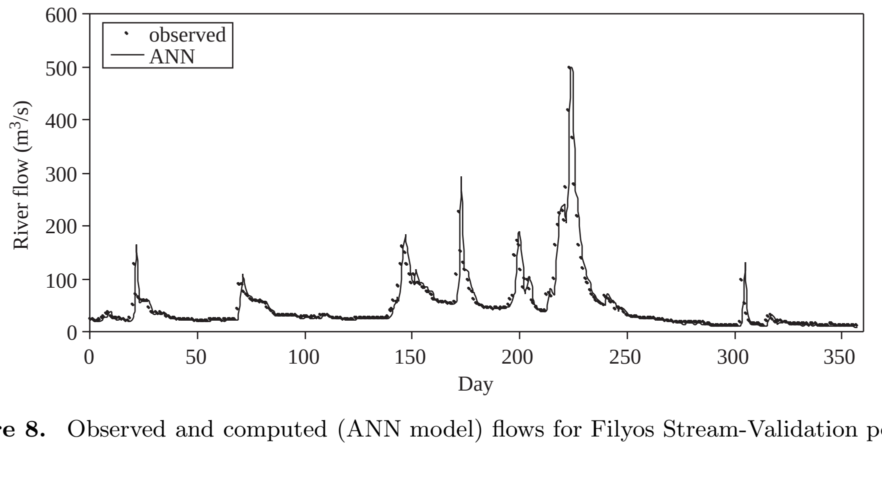

Figure 8. Observed and computed (ANN model) flows for Filyos Stream-Validation period.

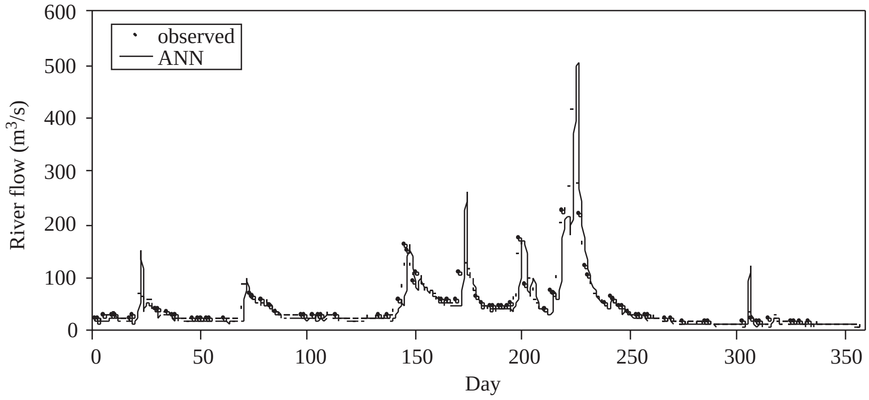

Figure 9. Observed and computed (AR model) flows for Filyos Stream-Validation period.

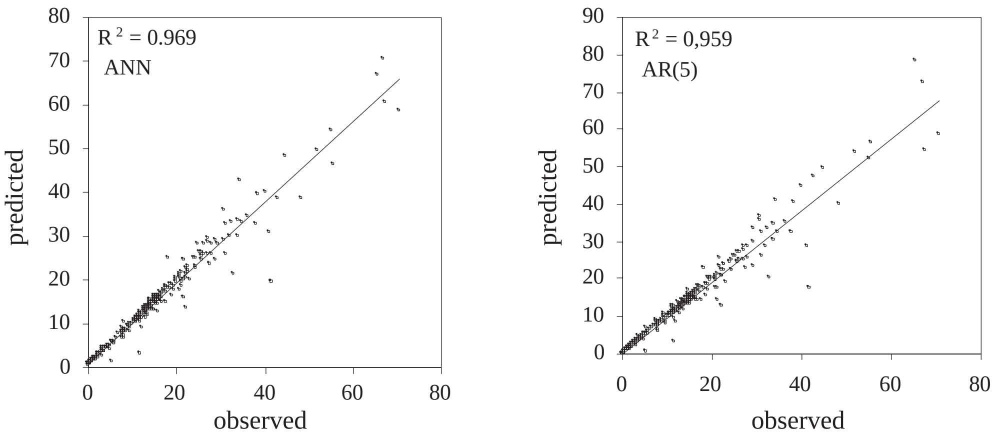

Figure 10. Scatterplots comparing predicted and observed flows for validation data of the Blackwater River.

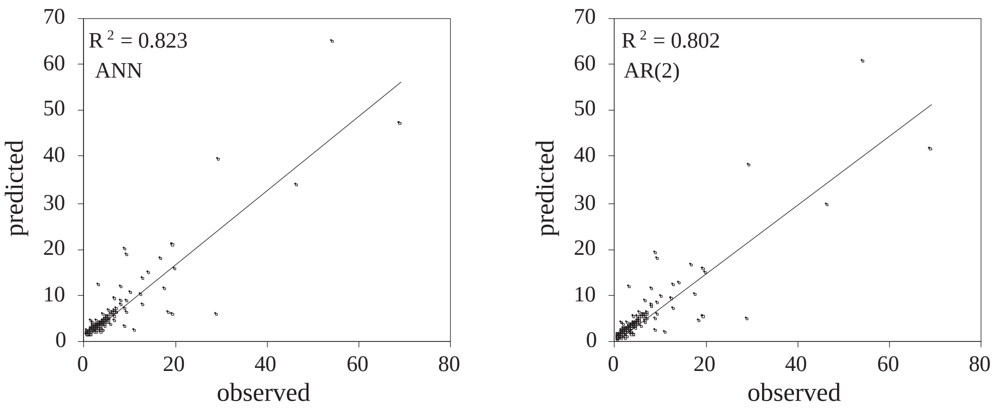

Figure 11. Scatterplots comparing predicted and observed flows for validation data of the Gila River.

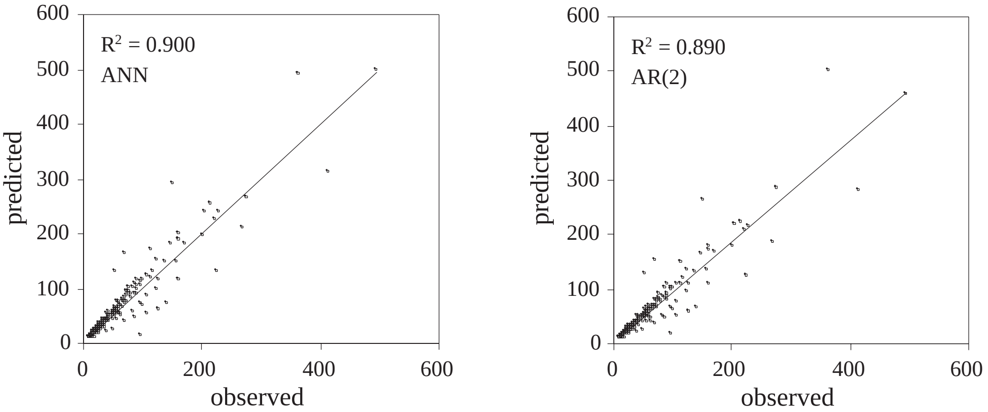

Figure 12. Scatterplots comparing predicted and observed flows for validation data of Filyos Stream.

Conclusions

The potential of ANN models for simulating the hydrologic behavior of streamflow has been presented in this study. The greatest difficulty lay in determining the appropriate model inputs for such a problem. Although ANNs belong to the class of data-driven approaches, it is important to determine the dominant model inputs, as this reduces the size of the network and consequently reduces the training times and increases the generalization ability of the network for a given data set.

The results obtained with ANNs for 1-day ahead forecasts are better than those reached in the AR models and confirm the ability of this approach to provide a useful tool in solving a specific problem in hydrology, that of streamflow forecasting. The results suggest that the ANN approach may provide a superior alternative to the AR models for developing input–output simulations and forecasting models in situations that do not require modeling of the internal structure of the watershed.

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