Research Article

Prediction of Missing Flow Records Using Multilayer Perceptron and Coactive Neurofuzzy Inference System

Samkele S. Tfwala, Yu-Min Wang, and Yu-Chieh Lin

Department of Civil Engineering, National Pingtung University of Science and Technology, Neipu Hsiang, Pingtung 91201, Taiwan

Correspondence should be addressed to Yu-Min Wang; wangym@mail.npust.edu.tw

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Hydrological data are often missing due to natural disasters, improper operation, limited equipment life, and other factors, which limit hydrological analysis. Therefore, missing data recovery is an essential process in hydrology. This paper investigates the accuracy of artificial neural networks (ANN) in estimating missing flow records. The purpose is to develop and apply neural networks models to estimate missing flow records in a station when data from adjacent stations is available. Multilayer perceptron neural networks model (MLP) and coactive neurofuzzy inference system model (CANFISM) are used to estimate daily flow records for Li-Lin station using daily flow data for the period 1997 to 2009 from three adjacent stations (Nan-Feng, Lao-Nung and San-Lin) in southern Taiwan. The performance of MLP is slightly better than CANFISM, having $R^2$ of 0.98 and 0.97, respectively. We conclude that accurate estimations of missing flow records under the complex hydrological conditions of Taiwan could be attained by intelligent methods such as MLP and CANFISM.

1. Introduction

Taiwan is situated on typhoon tracks with high temperatures and heavy rainfalls. There are over 350 typhoons and about 1000 storms that have attacked Taiwan over the past century and led to severe flood disasters. These events concentrate in the summer and autumn season (June to August), resulting in average annual precipitation of about 2500 mm and reaches 3000–5000 mm in the mountain regions. In addition, rivers in Taiwan are short with small drainage basins and steep slopes. During the above-said period, their peak flows are enormous; for example, a catchment area of about 2000–3000 km$^2$ often receives peak flows of up to 10000 m$^3$/s [1]. Consequently, measurement instruments installed in some stations are damaged resulting in data gaps. Field personnel may also attribute the data gaps to a number of factors such as malfunctioning of monitoring instrument, absence of observer, natural phenomena (e.g., earthquakes and landslides), and human induced factors like mishandling of observed records. These gaps and discontinuities lead to problems in planning of water development schemes, design of hydraulic structures, and management of water resources. In addition, challenges in the future may surface when a modelling system or a decision support system requires making use of this measured data. This necessitates filling the gaps.

Regression techniques have long been used for the generation of stream flow [2]. The idea is to model flow at one gauge as a function of flow at another gauge or gauges. Reference [3] compared regression and time-series techniques to synthesize and predict stream flow at downstream gauge from an upstream gauge in California. Reference [4] successfully filled in missing data, by extending single-output box-Jenkins transfer/noise models for several groundwater head series to a multiple-output transfer/noise models. However, such methods may not be suitable in Taiwan because of the complex hydrological system.

Artificial neural networks (ANN) are gaining popularity, especially over the last few years, in terms of hydrological applications. At the beginning early nineties, it has been successfully applied in hydrology related areas such as rainfall-runoff modelling [5, 6], stream flow forecasting [7, 8], ground water modelling [9], and reservoir operations and modelling [1, 10]. Reference [11] applied ANN and adaptive
neurofuzzy inference system (ANFIS) models to model and predict precipitation 12 months in advance. Reference [12] employed a distributed support vector regression model (D-SVR) equipped with genetic algorithm based artificial neural network (ANN-GA) as part of flood control measures. ANN has also been used successfully in water quality, water management policy, evapotranspiration, precipitation forecasting, and hydrological time series. Most hydrological processes exhibit temporal and spatial variability and are often plagued by issues of nonlinearity of physical processes and uncertainty in spatial estimates. The time and effort required in developing and implementing such complicated models may not be justified. Simpler neural network forecast may therefore seem attractive as an alternative tool.

Reference [13] compared six different types of ANN, namely, the multilayer perceptron network and its variation (the time lagged feed forward network), the radial basis function, recurrent neural network and its variation (the time delay recurrent neural network), and the counter propagation fuzzy neural network for infilling missing daily total precipitation. The results of their experiment revealed that the multilayer perceptron network could provide the most accurate estimates of the missing precipitation. In recent years, much attention has been given to derive effective data driven neurofuzzy models due to its numerous advantages [14]. Reference [15] modeled inflow forecasting of the Nile River using neurofuzzy model. Reference [16] applied neurofuzzy model for evapotranspiration modelling.

To the knowledge of the authors, no work has been reported in the literature that investigates the accuracy of multilayer perceptron (MLP) neural networks model and coactive neurofuzzy inference system model (CANFISM) in missing flow records. Hence, in this study, MLP and CANFISM are used to estimate daily flow records for Li-Lin station using daily flow data for the period 1997 to 2009 from three adjacent stations (Nan-Feng, Lao-Nung, and San-Lin). The above stations are located in the Kaoping river basin in southern Taiwan.

2. Materials and Methods

2.1. Study Area Characteristic. Kaoping River basin is located in the southern part of Taiwan at 22°12'30" North latitude and 120°12'00" East longitude and is shown in Figure 1. In this basin, four flow observation stations were selected and these are Nan-Feng Bridge, San-Lin Bridge, Lao-Nung, and Li-Lin Bridge. This river basin is the largest and most intensively used basin in Taiwan. It is Taiwan's second longest river with its 171 km length and drains a catchment covering 3,257 km² of land that is roughly 9% of the island's total area.

2.2. Neural Networks Model. An ANN is an information-processing paradigm inspired by biological nervous systems such as our brain [17]. Neural networks are composed of neurons as basic units. Each neuron receives input data, processes the input data, and transforms them into output forms. The input may be pure data or the output results of other neurons and the output forms may be the results of other neurons [18]. The neural networks used in the study (MLP and CANFISM) are managed by the Neurosolutions software version 5.07 presented by the Neurodimension and further descriptions are given below.

2.2.1. Multilayer Perceptron Neural Network. An MLP distinguishes itself by the presence of one or more hidden layers, with computation nodes called hidden neurons, whose function is to intervene between the external inputs and the network output in a useful manner. By adding hidden layers, the network is enabled to extract higher order statistics. The network acquires a global perspective despite its local connectivity due to the extra synaptic connections and the extra dimension of neural network interconnections. The MLP can have more than one hidden layer; however, studies have revealed that a single hidden layer is enough for ANN to approximate any complex nonlinear function [19, 20]. Therefore, in this study, one hidden layer MLP is used. MLP is trained using the many kinds of backpropagation algorithm.

The training performance is a process of adjusting the connection weights and biases so that its output can match the desired output best. Specifically, at each setting of the connection weights, it is possible to calculate the error committed by the network by taking the difference between the desired and actual responses [21, 22]. In this study, we use Quickprop backpropagation algorithm (BPA). The advantage of this algorithm is that it operates much faster in the batch mode than conventional BPA. In addition, it is not sensitive
Table 1: Conditions of the training performance variables for MLP.

| Training variables     | Assigned value |
|------------------------|----------------|
| Step size              | 1              |
| Momentum               | 0.5            |
| Iterations             | 5000           |
| Training threshold     | 0.001          |

Table 2: Conditions of the training performance variables for CANFISM.

| Training variables     | Assigned value |
|------------------------|----------------|
| Membership function    | Gaussian       |
| MFs per input          | 3              |
| Fuzzy model            | TSK            |
| Step size              | 1              |
| Momentum               | 0.5            |
| Iterations             | 1000           |
| Training threshold     | 0.001          |

2.2.2. Coactive Neurofuzzy Inference System Model. Coactive neurofuzzy inference system model (CANFISM) belongs to a more general class of adaptive neurofuzzy inference system model (ANFISM). It may be used as a universal approximator of any nonlinear function. In addition, it integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions. The characteristics of CANFISM are emphasized by the advantages of integrating neural networks with fuzzy inference in the same topology. The powerful capability of CANFISM stems from pattern-dependant weights between the consequent layer and the fuzzy association layer [23]. The fundamental component of CANFISM is a fuzzy node that applies membership functions to the input nodes. Two membership functions commonly used are bell and Gaussian. The network also contains a normalization axon to expand the output into a range of 0-1. The second major component of this type of CANFISM is a modular network that applies functional rules to the inputs. The number of modular networks matches the number of network outputs and the number of processing elements in each network corresponds to the number of membership functions. CANFISM also has a combiner layer that applies the membership functions outputs to the modular network outputs. Table 2 shows the conditions of the training performance variables of the CANFISM.

In this study, the CANFISM architecture used had three inputs and one output. The flow data from Nan-Feng Bridge, San-Lin Bridge, and Lao-Nung were used as inputs to the model and Li-Lin Bridge as output (Figure 3). From the 1283 patterns of data, 70% of the data were used for training, 20% for cross validation, and 10% for testing. The training performance of neural network is iterated until the training error is attained to the training tolerance. Iteration refers to a one completely pass through a set of inputs and target data.

2.3. Data Normalization. Preprocessing of the data is usually required before presenting the data samples to the neural network [6]. Hence, stream flow data of the stations used were normalized to prevent problems associated with extreme values. In this study, the data is scaled in the range (0-1) using the following equation:

\[ Y_{\text{norm}} = \frac{Y_i - Y_{\text{min}}}{Y_{\text{max}} - Y_{\text{min}}}, \]

where \( Y_{\text{norm}} \) is the scaled input value, \( Y_i \) is the actual unscaled observed flow input, and \( Y_{\text{min}} \) and \( Y_{\text{max}} \) refer to the minimum and maximum values of the data, respectively. In addition, some of the data were similar for some days in the different stations; these data was assumed incorrect, and therefore we discarded it.
2.4. Models Performance Evaluation. The performance of the neural networks models are evaluated using a variety of standard statistical indexes. In our study, we evaluated the models using three indexes, root mean square error (RMSE), mean absolute error (MAE), and coefficient of correlation \( R \). The RMSE is a measure of the residual variance. MAE measures how close forecasts or predictions are to eventual outcomes. The \( R \) is a measure of accuracy of a hydrological modelling and is generally used for comparison of alternative models.

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (y_i - y'_i)^2}{N}},
\]

\[
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} \| y_i - y'_i \|, \tag{2}
\]

\[
r = \frac{\sum_{i=1}^{N} (y_i - \bar{y})(y'_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (y_i - \bar{y})^2 \sum_{i=1}^{N} (y'_i - \bar{y})^2}},
\]

where \( y_i \) represents the observed flow record, \( y'_i \) is the alternative methods estimated flow values, \( \bar{y} \) and \( \bar{y}' \) represent the average values of the corresponding variable, and \( N \) represents the amount of data considered. Additionally, a linear regression \( y = \alpha_1 x + \alpha_0 \) is applied for evaluating the models’ performance statistically, where \( y \) is the dependent variable (alternative methods), \( x \) the independent variable (observed), \( \alpha_1 \) the slope, and \( \alpha_0 \) the intercept.

3. Results and Discussion

3.1. Processing Elements Determination. The determination of processing elements (PE) is one of the difficult tasks in neural network models [10, 21, 23]. In addition, it is an important factor, which affects the performance of the trained network [24]. Hence, determination of PEs was the initial process of the learning procedure. The number of PEs in the hidden layer was varied between 1 and 10 for the MLP. The data set aside for testing was used to find the optimal number of PEs. In this study, the number of optimum PEs was found at 8 based on the minimum RMSE and maximum \( R^2 \) as illustrated by Figure 4.

In CANFISM, however, the hidden layer and the processing elements do not exist in the structure. Instead,
3.2. Comparison of the Different Models. In the present study, flow records for one station are estimated using MLP and CANFISM from three adjacent stations located in the same catchment. The data used to develop these models was obtained from annual reports of the Taiwan Water Resources Agency, Taiwan. The prediction capabilities of these models were analysed by means of comparison with observed data. A summary of the models statistical performance during training, cross validation, and testing stage is shown in Table 3. From the evaluation of these results, MLP was found to show better statistics results compared to CANFISM in the cross validation and testing stage. The RMSE of MLP for cross validation and testing stage was 382.98 m$^3$/s and 150.36 m$^3$/s, respectively, while that for CANFISM was 388.97 (m$^3$/s) and 404.49 (m$^3$/s), respectively. Moreover, the $R^2$ of MLP in cross validation and testing was 0.83 and 0.98, respectively, while that for CANFISM was 0.81 and 0.97, respectively. Reference [23] made similar observations in the prediction of pan evaporation that MLP model was better than CANFISM.

CANFISM showed better results only in the training stage, having RMSE and $R^2$ of 388.97 (m$^3$/s) and 0.69 compared to that of MLP, having RMSE of 401.84 (m$^3$/s) and $R^2$ of 0.67. Figures 6 and 8 show the observed and estimated flows using MLP and CANFISM, respectively. The trends of the estimated flow are similar to the observed data, although at some places, slight differences are seen. The corresponding scatters for both MLP and CANFISM in the testing stage are shown in Figures 7 and 9. The higher accuracy attained by these models emphasizes the applicability of ANNs in estimating missing flow records.

4. Conclusion

Accurate estimation of missing flow records is an essential component in decision support system for efficient water management and future planning of water resources systems. The objective of the paper was to investigate the accuracy of...
artificial neural networks (ANN) in estimating missing flow records. The flow data of three stations was used to estimate flow data of one station. The potential of ANNs for estimating missing flow records has been demonstrated in this study with both MLP and CANFISM having higher $R^2$ of 0.98 and 0.97, respectively. In general, the findings of this study indicate that accurate estimations of missing flow records under the complex hydrological condition of Taiwan can be attained using MLP and CANFISM methods.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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