THE APPLICATION OF ARTIFICIAL NEURAL NETWORK ON THE RIVER FLOW FORECASTING IN YOUNG-SAN RIVER, SOUTH KOREA

Younghoon Jin Student Member Department of Civil Engineering, Kyushu University
Akira Kawamura Member Institute of Environmental Systems, Kyushu University
Kenji Jinno Member Institute of Environmental Systems, Kyushu University

1. Introduction

The conceptual modeling and the system theoretical modeling have been explored to model the rainfall-runoff process. However, the calibration of the conceptual models can typically present various difficulties, requiring sophisticated mathematical tools, significant amounts of calibration data. Therefore, a hydrologist implements a simpler system theoretical model. In this study, the artificial neural network approach that is applied to various sites is used to forecast the runoff of the river. It is effective that the applicability of the artificial neural network approach presents the non-linearity inherent in the rainfall-runoff process. The models of the artificial neural network are trained using the learning algorithm. In this paper, the back-propagation algorithm is utilized for training. The momentum constant and the adaptive learning rate are also applied to improve the effectiveness of training, and parameters are estimated with the selected model in this study. The results provide a better representation of the model.

2. Artificial Neural Networks (ANNs)

Artificial neural networks are parallel computing systems that originated from the structure and function of the brain. In this paper, feed-forward NNs were used for training by back-propagation algorithm with momentum constant and adaptive learning rate.

Feed-forward ANNs comprise a system of units, namely neurons, which are arranged in layers. The neurons perform two major functions that are summation of weighted inputs and transferring the summed data through the activation function. The log - sigmoidal function is used as the activation function in hidden layer and the pure linear function in output layer, respectively.

Generally, feed-forward ANNs include three layers that the first layer is called input layer, the second is hidden layer and the third is output layer. The units in each layer are connected to the units in a subsequent layer by weighs and biases, which may be adjusted during training.

The early stopping method for training is also used to improve the efficiency of training and to maintain the consistency of model between training, testing, and validation data set. Then, when the testing error increases for a specified number of iterations (100 epochs in this study), the training is stopped.

3. River Flow Prediction

3.1 Study Basin

The data from Young-San River in South Korea have been utilized for the present study. The Young-San River has a catchment area of 3,429 km^2. Naju and Sunam stations that are representatives of Young-San River basin were selected for river flow prediction in this study. The catchment areas of Naju and Sunam stations are 2,058.72 km^2 and 526.56 km^2, respectively.

3.2 Data Used

Five years of daily rainfall and runoff data (1993 to 1998, excepting 1995 that has many missing value) are available for Naju station. The areal averaged precipitation is computed using Theissen polygon method with the data of a number of gauging stations located within the catchment of the Young-San River.

In Sunam station, however, both of daily and hourly data were used for the runoff forecasting. Because of moving of the Sunam station in 1996 year, it was recommendable to use the rainfall and runoff data between 1997 and 1998 year. The original rainfall data at the upstream gage stations not calculated by Theissen polygon method.

It is needed to divide the available data into three subsets for training, testing, and validation. The used data period for each procedure is presented in Table 1.

Table 1. The data period used for training, testing, and validation in Naju and Sunam station.

Station	Naju	Sunam	Sunam
Unit	Day	Day	Hour
Training Period	1996~1997 (01,Jun.~31,Oct.)	1997 (01,Jun.~31,Oct.)	1997-08-05
Testing Validation Periods	1998 1993~1994 (01,Jun.~31,Oct.)	1998 (01,Jun.~31,Oct.) No Validation	1998-08-18 1998-09-29

4. Scaling and Model Construction

4.1 Scaling

Data pre-processing can have a significant effect on model performance. In order to ensure that all variables receive equal attention during the training process, they should be standardized. In this study, the network input and target values are normalized by the mean and standard deviation of the training set as following equation :

$$Z = (X_i - \mu)/\sigma$$

in which X_i is the i th data, μ and σ represent the mean value and standard deviation, respectively.

After training, the outputs should be converted into the same units which were used for the original targets using post-processing.

4.2 Model Construction

The daily runoff forecasting is performed in Naju station and the hourly and daily runoff are predicted in Sunam station using ANNs. However, the optimum architecture of ANNs is generally found by a process of trial and error, an approach which is somewhat frustrating and time-consuming.

In this paper, several models with lagged time of rainfall and runoff is constructed and then the number of nodes in hidden layer increases from the number of input nodes to treble number of input nodes with only one output node. In the daily runoff forecasting of Naju station, the input variables are the runoff and the areal averaged precipitation with lag times that are selected between 1 and 5 days for each models. Also, in the daily forecasting of Sunam station, the runoff and the areal averaged precipitation with lag times from 1 to 2 days are applied to the model.

However, for the hourly runoff forecasting in Sunam station, the data of upstream 5 rain gage stations are used to construct two models. The first model is composed by the runoff with lag times from 1 to 3 hours and the rainfall data with lag times from 4 to 6 hours for each rain gage stations. The second model also has the same runoff data and the rainfall data with lag times from 5 to 7 hours. So, the ANNs of both models have the 15 input nodes.

A number of best model architectures are selected by following performance criteria, for each case study. The values of momentum constant and initial adaptive learning rate are also configured with 0.7 and 0.9, respectively.

5. Performance Criteria and Results

5.1 Model Evaluation Criteria

The model evaluation criteria are grouped as graphical and the numerical performance indicators, proposed by World Meteorological Organization. Suitable ones of a number of numerical indicators of WMO for this study are presented and they are the root mean squared error (RMSE) and the R^2.

5.2 Results

5.2.1 Daily Runoff Forecasting in Naju Station

The results of daily forecasting of Naju station present the values of R^2 between 0.909 and 0.915 in training data set, and 0.909 and 0.916 in testing data set. However, in validation data set, the values of R^2 were decreased to be 0.802 and 0.858.

5.2.2 Daily Runoff Forecasting in Sunam Station

The values of R^2 in Sunam station vary from 0.989 to 0.993 in training subset, and from 0.876 to 0.907 in testing subset. However, the validation was not performed because the Sunam station did not have enough data to separate the available data into three subsets.

5.2.3 Hourly Runoff Forecasting in Sunam Station

The best results are presented in hourly forecasting of Sunam station with the values of R^2 from 0.9996 to 0.9998 in training, 0.9528 to 0.9671 in testing, 0.9865 to 0.9870 in validation subset.

The ANN(15,19,1) was selected to predict the runoff in Sunam station with one of the highest values of R^2 efficiency. This model is composed of 15, 19, 1 neurons for each layer. The ANN(15,28,1) also show the one of highest values, but in this paper, only the hydrographs of the graphical indicators are presented from Fig. 1 and Fig. 3, for the ANN(15,19,1) model.

In following hydrographs, the observed data are provided by solid line and the hollow circle shows the simulated data.

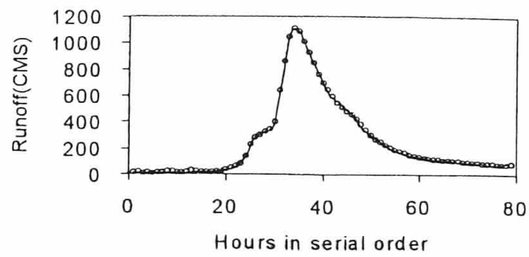

Fig. 1. The hydrograph of training data in Sunam station

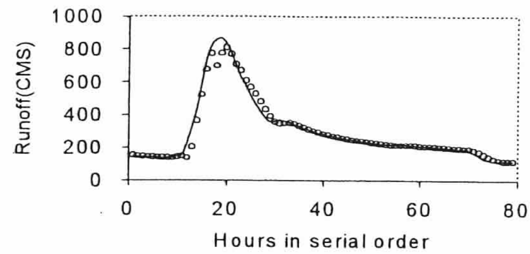

Fig. 2. The hydrograph of testing data in Sunam station

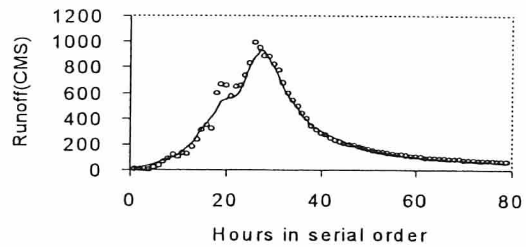

Fig. 3. The hydrograph of validation data in Sunam station

6. Conclusion

In this study, the ANNs was applied to the daily and hourly runoff forecasting of Naju and Sunam station, in the Young-San River, South Korea. The ANNs were configured with 0.7 of momentum constant and 0.9 of initial learning rate, and included the early stopping method of training for improving the efficiency and maintaining the consistency of the selected model.

Generally, the results of the selected models present good values of R^2 efficiency and RMSE in the daily runoff forecasting of Naju and Sunam station. Even though the results show the over- and under estimation in some data, especially peak data of runoff, the results of hourly runoff forecasting of Sunam station are superior to daily forecasting in the numerical indicators. It might be considered because the artificial intervention, such as Theissen method, to calculate the areal average rainfall data was eliminated from input data.

References

1. N.Sajikumar, B.S.Thandaveswara, 1999. A non-linear rainfall-runoff model using an artificial neural network. J. of Hydrol. 216, 32-55.