Streamflow Analysis using Stochastic and ANNs Approaches in the Parallel Reservoir Groups, South Korea.

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1. Introduction

Artificial neural networks(ANNs) have proven to be an efficient alternative to traditional method for modeling qualitative and quantitative water resources variables. Recently, numerous ANNs-based rainfall-runoff models have been proposed to forecast streamflow, drought analysis, and reservoir streamflow(Kim, 2000a; Kim and Cho, 2002b; Jain et al., 1999; Coulibaly et al., 2000a). The main advantage of the ANNs approaches over traditional methods of modeling is that it does not require the complex nature of the underlying process under consideration to be explicitly described in mathematical terms. Most of ANNs application cases in water resources have used the conventional feedforward neural networks, namely the standard multilayer perceptron(MLP) trained with the backpropagation algorithms. This paper evaluates Spatial-Stochastic Neural Networks Model(SSNNM) in long-term streamflow estimation. The aim of study is to estimate long-term streamflow using SSNNM in Andong and Imha parallel reservoir groups of the Upper Nakdong River. The input data in the SSNNM were composed with hydrologic and climatic factors such as monthly mean streamflow with 1 month-lead time, monthly mean precipitation, monthly pan evaporation, and monthly mean temperature terms. SSNNM could calculate monthly mean streamflow of Andong and Imha parallel reservoir groups simultaneously even if there are temporal and spatial variability of the entire input data field. The new approaches gave outstanding results throughout model calibration and validation. SSNNM will help to manage and control water distribution and contribute basic hydrologic data for long-term coupled operation in parallel reservoir groups of the Upper Nakdong River, South Korea.

2. The Structure in SSNNM

SSNNM was developed by the MATLAB Version 6.0 code sources produced by the MathWorks Inc.(Demuth and Beale, 2000). The type of SSNNM was formed a kind of multilayer perceptron in the structure, which is composed of input, hidden, and output layer, using LMBP and BFGS-QNBP algorithm. The major difference of structure and formation between SSNNM and any other neural networks based model is that SSNNM embeds stochastic approaches in training data because of insufficient time series. Measurements of streamflow(Q), precipitation(P), pan evaporation(E) and temperature(T) can be obtained easily and cost effectively as compared with those of soil characteristics, initial soil moisture, infiltration and groundwater characteristics. Therefore, a model that uses available real-time data would be more easily applied in the

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operational systems. The data variables of input layer, monthly mean streamflow with 1 month-lead time $(Q(t-1))$, monthly mean precipitation $(P(t))$, monthly pan evaporation $(E(t))$, and monthly mean temperature $(T(t))$ were selected to describe the physical phenomena of the input-output processes to estimate long-term streamflow into Andong and Imha parallel reservoir groups. The results of output layer, monthly mean streamflow $(Q(t))$ in Andong and Imha reservoir, can be written as following equation [1]. Figure 1 shows proposed SSNNM structure in this study

$$Q(t_a, t_i) = \Phi_2(\sum_{k=1}^{2} W_{kj} \cdot \Phi_1(\sum_{j=1}^{8} W_{ji} \cdot X(t) + B_{1j}) + B_{2k}) \qquad [1]$$

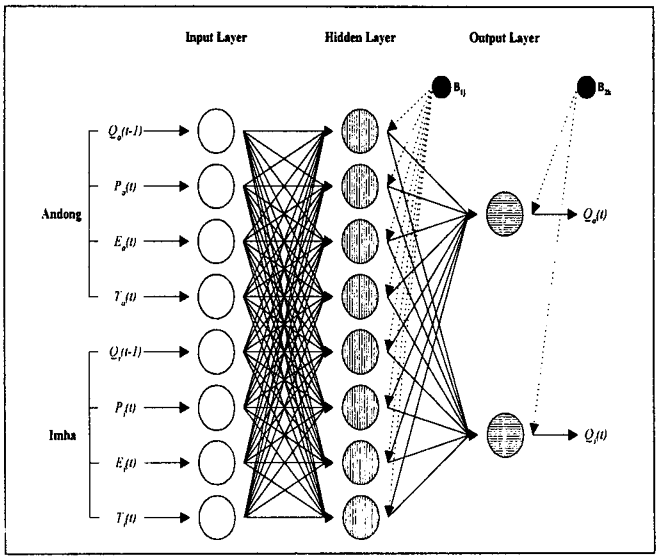

Figure 1. Proposed Spatial-Stochastic Neural Networks Model Structure

3. Study Area and Data

Andong multivariate reservoir, one of study basins, is located at the Upper Nakdong River and has 1,584.0 km^2 drainage areas which is 20% of the Total Nakdong River. Imha multivariate reservoir is located at the upper 18km from the confluence of the main Nakdong River and the tributary Banbyeon. They have played an important role to supply water, generate hydropower, and control flood(MOCT, KOWACO, 1991, 1999). Data for this study were composed of hydrologic and meteorological data such as monthly mean streamflow, monthly mean precipitation, monthly pan evaporation, and monthly mean temperature terms taken from Andong and Imha parallel reservoir groups

4. Training of SSNNM

4.1 Generation of Training Data

For model training and validation, the number of data has to be sufficient to use for the purpose of stability and reliability of analysis. In general, short time series for analysis have to be generated using stochastic or statistical model. Insufficient data that are monthly mean streamflow, monthly mean precipitation, monthly pan evaporation, and monthly mean temperature were generated using periodic autoregressive moving average stochastic model. In other words, we call it PARMA stochastic model. Lower-order PARMA models, for example PARMA(1,1), are useful for modeling periodic hydrologic time series. PARMA(1,1) stochastic model is simply written as following equation [2].

$$y_{\nu,\tau} = \mu_\tau + \varphi_{1,\tau}(y_{\nu,\tau-1} - \mu_{\tau-1}) + \varepsilon_{\nu,\tau} - \theta_{1,\tau}\varepsilon_{\nu,\tau-1} \quad [2]$$

Where, ν = the number of year, τ = the number of season and $\tau = 1,2,3\Lambda\ \omega$. This stochastic model has been applied to monthly streamflow series(Salas et al., 1980). Especially, SAMS(Salas J. D., 1998) program package was used to generate data in this study. The number of season is composed of 12 months, the number of samples that are generated is composed of 2 sets, and the length of years that are generated is composed of 100 years. The first half of 100 years in 2nd set was abandoned to eliminate biases and the latter 50 years were selected to train SSNNM.

4.2 Training for Optimal Parameters Estimation

The method for estimating parameters is generally called training in ANNs category. Parameters are modified iteratively to minimize the error until convergence is reached. The final connection weights and biases vector of a successfully trained ANNs based model represents its knowledge about problem. The training tolerance that mean square error is converged to a certain value was fixed with 0.001. The training procedure was iterated until the error is reached to training tolerance. Because the initial values were set random; the training results were slightly distinct whenever the training is completed. So the optimal parameters were determined when the training results shows the best categories during each iteration.

5. Validation of SSNNM

5.1 Validation of SSNNM with Optimal Parameters

All of parameters, optimal connection weights and biases that were selected during model training, were used to validate SSNNM. Data for validation were formed with observed and the contemporaneous time series from 1993 to 1999 such as monthly mean streamflow, monthly mean precipitation, monthly pan evaporation, and monthly mean temperature. In case of monthly pan evaporation, the extended data by the BRAM were used to validate. The streamflow estimation of Andong multivariate reservoir was found to yield slightly better results than that of Imha multivariate reservoir like the results of training. And, LMBP-SSNNM was found to yield better results than BFGS-QNBP-SSNNM in terms of statistical analysis. Figure 2 represents the comparison of hydrograph between observed and calculated monthly mean streamflow(Andong).

6. Summary and Conclusions

Spatial-Stochastic Neural Networks Model(SSNNM) was used to estimate long-term streamflow in the multivariate reservoir groups of the Upper Nakdong River, South Korea. For the SSNNM training procedure, the training sets in input layer were generated by the PARMA(1,1) stochastic model and they covers insufficient time series. Generated data series were used to train SSNNM and the model parameters, optimal connection weights and biases, were calculated during training procedure. Optimal parameters were applied to evaluate model validation using observed data sets. In general, the experimental results indicated that LMBP-SSNNM is more effective at estimating the hydrologic sequences than BFGS-QNBP-SSNNM. In turn, SSNNM showed the effectiveness for estimation of accurate streamflow and provided reliable alternatives to develop better hydrosystem management and planning.

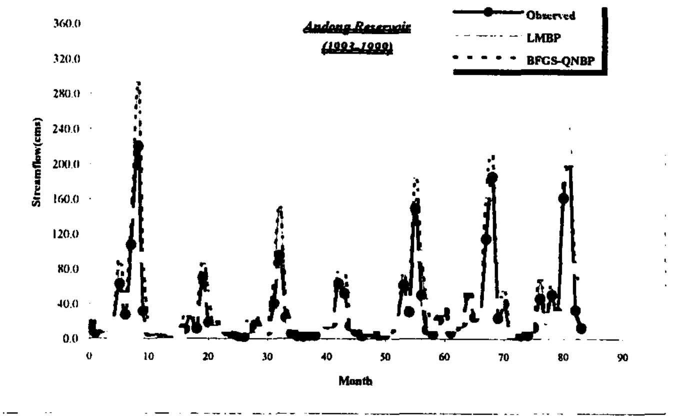

Figure 2. Comparison of Monthly Mean Streamflow Hydrograph(Andong, Validation)

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