Short-Term Hydrological Forecasting using Recurrent Neural Networks Model

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Abstract

Elman Discrete Recurrent Neural Networks Model(EDRNNM) was used to be a suitable short-term hydrological forecasting tool yielding a very high degree of flood stage forecasting accuracy at Musung station of Wi-stream, one of IHP representative basins in South Korea. A relative new approach method has recurrent feedback nodes and virtual small memory in the structure. EDRNNM was trained by using two algorithms, namely, LMBP and RBP. The model parameters, optimal connection weights and biases, were estimated during training procedure. They were applied to evaluate model validation. Sensitivity analysis test was also performed to account for the uncertainty of input nodes information. The sensitivity analysis approach could suggest a reduction of one from five initially chosen input nodes. Because the uncertainty of input nodes information always result in uncertainty in model results, it can help to reduce the uncertainty of EDRNNM application and management in small catchment.

Key words : EDRNNM, short-term forecasting, training, validation, sensitivity analysis.

1. Introduction[1]

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(Zealand et al., 1999; Liong, et al., 2000; Kim S., 2004; Kim et al., 2001, 2002a, 2003; Shin and Park, 1999; Coulibaly et al., 2000a, b). 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.

In this paper, Elman Discrete Recurrent Neural Networks Model(EDRNNM) is applied to forecast, for different lead hours, the flood stage at Musung station(No.1), Wi-stream of South Korea, based on flood stages measured at various upstream gauging stations. The model parameters, optimal connection weights and biases, are estimated during training procedure with Case 1-5 events. They are applied to evaluate model validation with Case 6-10 events. For the uncertainty analysis of input nodes information, sensitivity analysis tests are also conducted using the data of gauging station. The sensitivity analysis serves to eliminate gauging stations that insignificantly affect changes in the flood stage at Musung station(No.1).

2. The architecture of EDRNNM

The major difference of structure and formation between EDRNNM and any other neural networks based

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model is that EDRNNM has recurrent feedback nodes in the neural networks. When the output of a node is fed back into a node in an earlier layer, the output of that node is a function of both the inputs from the previous layer at time ***(t)*** and its own output that existed at an early time ***(t-Δt).*** Such neural networks exhibit characteristics similar to short-term memory, because the output of neural networks depends on both current and prior inputs. Neural networks that contain such feedback are called ***recurrent neural networks***(Tsoukalas and Uhrig, 1997). Elman Discrete Recurrent Neural Networks Model(EDRNNM), a special type of recurrent neural networks, is applied to forecast flood stage in this study. EDRNNM consists of a three layer networks with feedback only from the hidden layer output to the hidden layer input. This recurrent connection allows EDRNNM to both detect and generate time-varying patterns. For the forecasting of flood stage using EDRNNM, The results of output layer, $ST_1(t)$**,** can be written as following equation [1]. Figure 1 represents the proposed Elman Discrete Recurrent Neural Networks Model.

$$ST_1(t) = \Phi_2[[\sum_{k=1}^{1} W_{kj} \cdot \Phi_1((\sum_{j=1}^{5} W_{ji} \cdot X(t)) + (\sum_{j=1}^{5} W_{ij} \cdot (\Phi_1(\sum_{j=1}^{5} W_{ji} \cdot X(t-\alpha)))) + B_{1j}] + B_{2k}] \qquad [1]$$

Where ***i, j, k*** = input, hidden and output layer of EDRNNM ; $ST_1(t)$ = flood stage(m) at Musung station(No.1); $\Phi_1(\cdot)$ = hyperbolic tangent sigmoid transfer function in hidden layer ; $\Phi_2(\cdot)$ = log-sigmoid transfer function in output layer; W_{ji} = connection weights between input and hidden layer; W_{kj} = connection weights between hidden and output layer; W_{ij} = connection weights between recurrent nodes and hidden layer; B_{1j} = biases in hidden layer; B_{2k} = biases in output layer; $X(t-\alpha)$ = variables, flood stage with different lead hours, in input layer; and α = number of lead hours from 1 to 7hr.

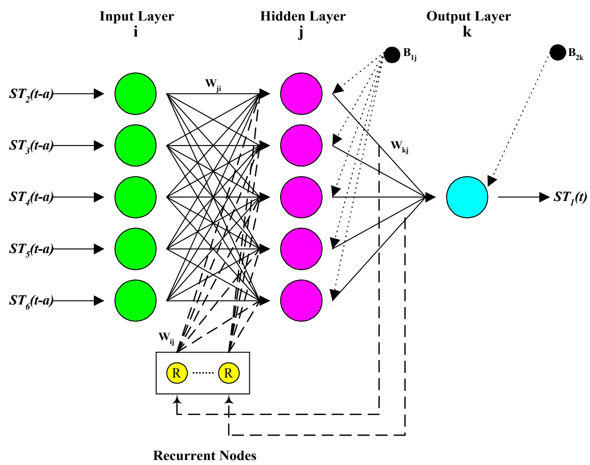


Figure 1. Proposed EDRNNM Structure.

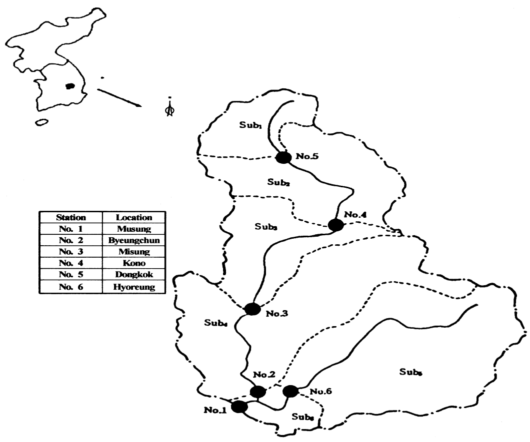


Figure 2. Schematic Diagram of Wi-stream

3. Study Area and Data

Wi-stream, one of IHP representative small catchments in South Korea, is located at the middle of Nakdong River. It has been observed hydrological data, such as precipitation, river stage, discharge, and groundwater, since 1982. Figure 2 shows schematic diagram of Wi-stream catchment in South Korea. Measurement of precipitation, air temperature, discharge, and river stage can be obtained easily and cost effectively as compared with that 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 operational forecasting systems(Tokar and Johnson, 1999). The training data should be large enough to contain the characteristics of flood stage and to accommodate the requirements of the EDRNNM. If the information included in the training data set is insufficient, an increase in the complexity of EDRNNM will not enable EDRNNM to generalize the patterns in the physical phenomena. For this reason, the data are selected with ten flood stage events(Case 1-10) randomly from 1980s to 1990s in this study. The events from Case 1 to Case 5 are used for model training. And, the rest, Case 6 - 10, apply to model validation.

Table 1. Flood Stage Events for This Study

Events	Dates	Duration(hr)	Maximum Level(m)
Case 1	83/06/20 00:00 - 06/24 18:00	114	3.11
Case 2	84/04/18 04:00 - 04/20 13:00	57	2.33
Case 3	85/08/17 01:00 - 08/19 08:00	56	3.94
Case 4	86/07/21 07:00 - 07/23 05:00	46	2.30
Case 5	87/07/14 19:00 - 07/18 03:00	80	5.03
Case 6	88/07/13 18:00 - 07/17 04:00	82	3.63
Case 7	89/08/21 11:00 - 08/24 21:00	82	3.41
Case 8	90/06/19 17:00 - 06/22 21:00	76	2.65
Case 9	91/07/07 07:00 - 07/13 05:00	142	2.39
Case 10	92/07/12 06:00 - 07/14 08:00	50	2.48

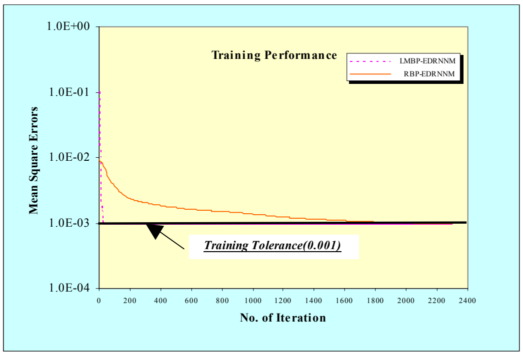


Figure 3. Training Performance of MSE

4. Training and Validation of EDRNNM

4.1 Model Training

The method for estimating parameter 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 model represent its knowledge about problem. In this study, 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. The performance of forecasting resulting from both the training and validation was evaluated following measure for goodness-of-fit; ***RMSE, R2, m(e), and CC***. The results of statistical analysis show very excellent in both LMBP-EDRNNM and RBP-EDRNNM. Figure. 3 shows training performance of mean square error in LMBP-EDRNNM and RBP-EDRNNM. And, figure 4 represents the comparison of flood stage hydrograph using Case 1.

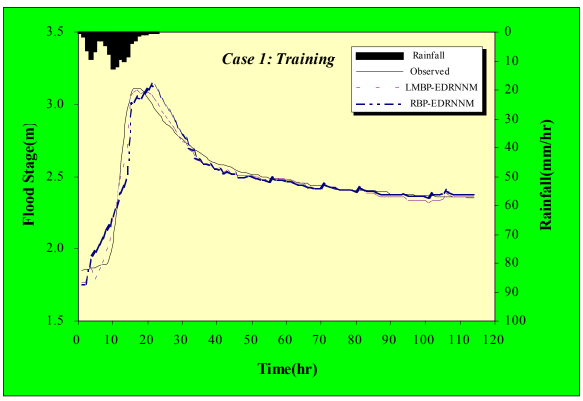


Figure 4. Comparison of hydrograph(Training)

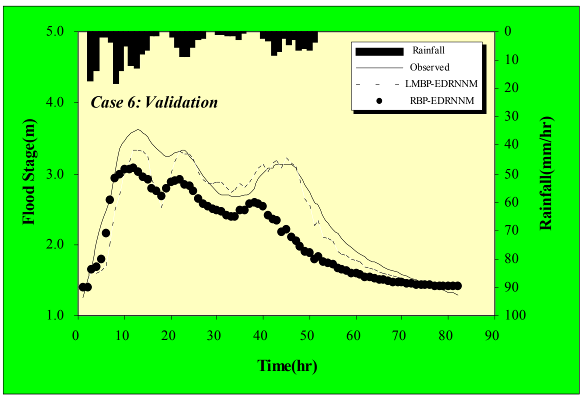


Figure 5. Comparison of hydrograph(Validation)

4.2 Model Validation

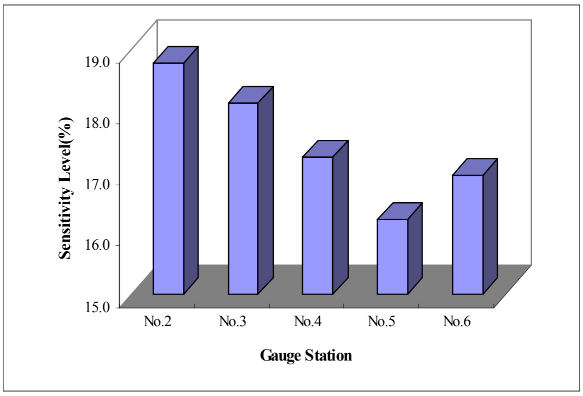
All of parameters, optimal connection weights and biases that were calculated during model training, were used to validate EDRNNM. The data during Case 6-10 were used for model validation. As the results of model validation, LMBP-EDRNNM was found to yield better results than RBP-EDRNNM in terms of statistical analysis and flood stage hydrograph. Figure 5 represents comparison of flood stage hydrograph using Case 6.

5. Sensitivity Analysis

Sensitivity analysis test is carried out to determine the relative significance of each of the input nodes. Reduction of input nodes would result in a decrease in unnecessary data collection that in turn lead to cost reduction. Step-by-step sensitivity analysis test was carried out using validation data by varying each of input nodes, one at a time, at a constant rate. Various constant rates(-20, -15, -10, -5, and 5%) are selected in this study. For every input node, the percentage change in the output, as a result of the change in the input nodes, was observed. The sensitivity of each input node is calculated by the following equation [2].

$$\text{Sensitivity Level of } \boldsymbol{X_i(\%)} = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{V_y}{V_x}\right)_j \times 100 \qquad [2]$$

Where V_x = % change in input nodes; V_y = % change in output node ; and N = number of data sets used in this study. Results show that the change in output node is unaffected by the rate that the input node is varied. Figure 6 and 7 show how sensitive the flood level changes at each of the gauging stations and how they will affect the changes in flood level at Musung station(No.1). Dongkok station(No.5) has an insignificant impact on Musung flood stage. Dongkok(No.5) is then eliminated from the input nodes. Thus the total number of input nodes reduces to four. A similar sensitivity analysis test was again carried out on the model with four input nodes. Results show that elimination of gauging station insignificantly affects changes in the flood stage at Musung station(No.1).



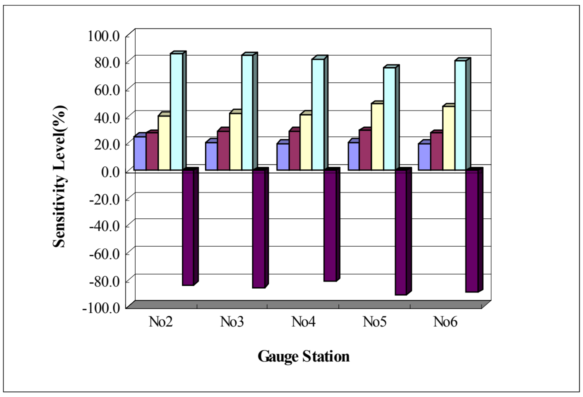


Figure 6. Sensitivity Levels of Input Gauge Station(a) **Figure 7. Sensitivity Levels of Input Gauge Station(b)**

6. Summary and Conclusion

In this study, EDRNNM was developed to forecast flood stage at Musung station(No.1) of Wi-stream, South Korea. EDRNNM employed two kinds of backpropagation algorithms, based on LMBP and RBP respectively. Cases 1-5 were used to train EDRNNM and model parameters, optimal connection weights and biases, were calculated during training procedure. They were applied to evaluate model validation using Cases 6-10. The flood stage forecasting obtained has a very high degree of accuracy even for a 7-lead-hour. In general, the experimental results indicated that LMBP-EDRNNM is more effective in forecasting flood stage than RBP-EDRNNM. It is important to determine the dominant input nodes, because this reduces the size of EDRNNM and consequently reduces the unnecessary data collection. Sensitivity analysis test has been introduced to verify the importance of each of the input nodes information. This leads to the elimination of one less sensitive input node. The removal of the less sensitive input node insignificantly reduces the accuracy degree of EDRNNM with four input nodes. Therefore, this study shows an operational technique for detecting less sensitive input nodes in an effort to reduce unnecessary data collection and high cost.

7. References

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