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Monthly Runoff Estimation Using Artificial Neural Networks

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ABSTRACT

Runoff estimation is one of the main challenges encountered in water and watershed management. Spatial and temporal changes of factors which influence runoff due to heterogeneity of the basins explain the complicacy of relations. Artificial Neural Network (ANN) is one of the intelligence techniques which is flexible and doesn't call for any much physically complex processes. These networks can recognize the relation between input and output. In this study ANN model was employed for runoff estimation in Plaszjan River basin in the central part of Iran. The models used are Multiple Perceptron (MLP) and Recurrent Neural Network (RNN). Inputs include data obtained from 5 rain gauges as well as from 2 temperature recording gauges, the output of the model being the monthly flow in Eskandari Hydrometric Station. Preprocessing of the data as well as the sensitivity analysis of the model were carried out. Different topologies of Neural Networks were created with change in input layers, nodes as well as in the hidden layer. The best architecture was found as 7.4.1. Recurrent Neural Network led to better results than Multilayer Perceptron Network. Also results indicated that ANN is an appropriate technique for monthly runoff estimation in the selected basin with these networks being also of the capability to show basin response to rainfall events.

Keywords: Artificial Neural Networks, Monthly rainfall–runoff models, Runoff estimation.

INTRODUCTION

Neural networks are widely regarded as potentially effective approaches to handling out vast amounts of dynamics the underlying physical relationships of which are not fully understood (Gorindaraju and Rao, 2000; Gorindaraju, 2000; Mahnaj, 2002). The application of ANNs to water resources problems is rapidly gaining popularity due to their immense power and potential in the mapping of non-linear systems (French *et al.,* 1992; Vladan and Christian, 1998; Singh and Woolhiser, 2002). A water resources system may be nonlinear and multivariate, and the variables involved having complex interrelationships (Bhattacharya *et al*., 2003; Maier and Dandy, 2000; Kingstone, 2003). Such problems can be effectively solved using ANNs. Neural networks are also particularly well suited for modeling systems on a real-time basis, and this could be used in hydrological forecasting systems (Bazartseren *et al*., 2002). ANN Performance is related to accurate real-time data inputs, the quality of the knowledge used to specify, build and operate the models as well as the ability of the models to respond to dynamic and sometimes rapidly changing events. There have been many studies having used neural networks in prediction as well as analysis in hydrological arenas, especially rainfall-runoff modeling. Jagadeesh *et al*. (2000) evaluated different neural networks for monthly runoff estimation in three basins

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in Kanzas State. They compared the results with those found through empirical methods. Results indicated a more capability of neural networks than the empirical methods. Comoplo *et al.* (1999) used neural networks for analyzing and predicting Taglimanto River responses. The inputs included data from 7 rainfall recording gauges, the output being monthly runoff. This model possesses the suitable accuracy for hour time steps, but the error, increases with increment in time steps. Drecourt (1999) used a model of neural networks for rainfall-runoff modeling and indicated that this kind of black box is capable of decreasing errors. Kumar *et al*. (2001) used two models of neural networks namely feedforward and recurrent neural networks for a prediction of monthly flow of a river in India. Results indicated that recurrent neural networks performed better than the feedforward neural networks. In this study, two types of ANNs were employed namely: multilayer perceptron and time lagged recurrent networks.

MATERIALS AND METHODS

Multilayer Perceptron Networks

The multilayer perceptron is one of the most widely implemented neural network topologies. In terms of mapping abilities, MLP is believed to be capable of approximating arbitrary functions (Kisi, 2005; Madson *et al*., 2000). This has been important in the study of nonlinear dynamics, and in other functional mapping problems. In backpropagation learning the system response at PEi (Perceptron Element) at iteration n, $y_i(n)$, and the desired response $d_i(n)$ for a given input pattern of an instantaneous error $e_i(n)$ is defined by:

$$e_i(n)= d_i(n)-y_i(n) \qquad (1$$

$$w_{ij}\left(n+1\right)=w_{ij}(n)+\eta\partial_i(n)x_j(n) \qquad (2$$

Using the theory of gradient descent learning, each weight in the network can be adapted by correcting the present value of the weight with a term that is proportional to the present input and the error at the weight. In Equation (2) the local error $\partial_i(n)$ can be directly computed from $e_i(n)$ at the output PE or can either be computed as a weighted sum of errors at the internal PEs. The constant η is called the step size.

Recurrent Neural Networks

The classes of neural networks which contain cycles or feedback connections are called Recurrent Neural Networks (RNNs). While the set of topologies of a feedforward network is fairly constrained, a RNN can take on any arbitrary topology as any node in the network may be linked with any other node (including itself). Time Lagged Recurrent Networks (TLRNs) are MLPs extended with short term memory structures (Coulibaly *et al.*, 2001; Kumar *et al.*, 2001). Most real-world data contains information in its time structure, i.e. how the data changes with time. The most studied TLRN network is the Gamma model. The Gamma model is characterized by a memory structure that is a cascade of leaky integrators, i.e. an extension of the context unit of the Jordan and Elman nets. The signal at the taps of the Gamma memory can be represented by:

$$x_O(n)=u(n) \qquad (3$$

$$x_k(n)=(1-\mu)(x_k)(n-1)+\mu x_{k-1}(n-1) \qquad (4$$

$k= 1, 2,\ldots K$

Note that the signal at tap k is a smoothed version of the input which holds the voltage of a past event, creating a memory.

Study Basin, Database and Modeling Methods

Plasjan basin located at 50˚ 2´ to 50˚ 41´ longitude and 32˚ 12´ to 32˚ 46´ latitude with an area of 1,644 km^2 is a part of Zayandehrud Dams basin. The elevation of study area ranges from 2,136 to 3,669 meters with an average of 2,560 meters. Mean annual rainfall is about 462 millimeters. Plasjan River with a 60 km length is the major river

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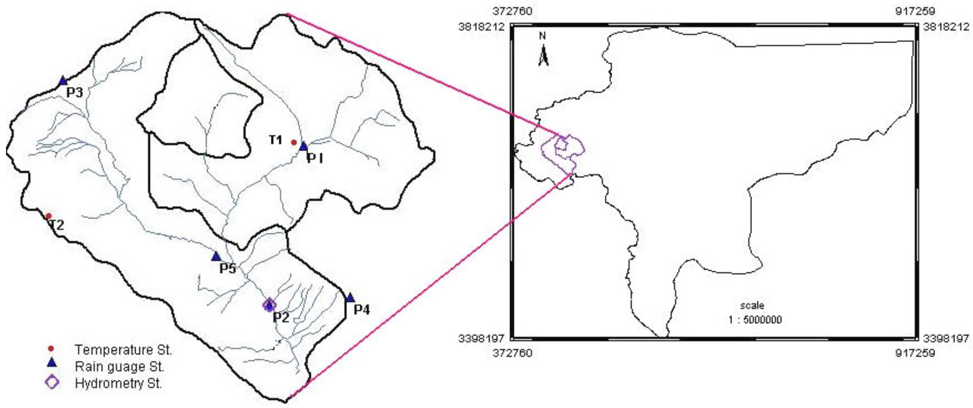

Figure 1. Study area and selected stations.

of the catchment with 4.5 $m^3 s^{-1}$ mean annual discharge, gauged at Eskandari Station at the outlet of the basin (Yazdani and Chavoshi, 2005). There are 5 rain gauges and 2 temperature recording stations inside as well as outside the basin (Figure 1).

Monthly data of discharge was selected from Eskandari Station located near the basin outlet and from P_2 rain gauge. Data was selected in the same period, from October 1975 to September 1998. Preprocessing of the data was run, the homogeneity test of data being performed and the missing data corrected for.

Two kinds of neural networks, namely Multilayer Perceptron and Time Lag Recurrent Networks were employed. Input data included mean monthly rainfall from 5 rain gauges (P_1, P_2, P_3, P_4 and P_5) and mean monthly temperature of 2 temperature recording stations (T_1 and T_2) with output being the monthly discharge (Q) at Eskandari Hydrometry. Then data were divided into 3 sets, including training (216 samples), cross validation (CV) (36 samples) and test (36 samples). Several topologies were taken into account for each model. With change in hidden layers, perceptron elements, learning rate, momentum, and activation function, different topologies were created and compared based on error. Three criteria were for on assessment of errors: mean square error (MSE), normalized mean square error (NMSE) as well as correlation coefficient (r). Version 4 of the neurosolution software was made use of in the study.

Table1. Some statistics of observed data.

Statistics	P_1 (mm)	P_2 (mm)	P_3 (mm)	P_4 (mm)	P_5 (mm)	T_1(°C)	T_2 (°C)	Q ($m^3 s^{-1}$)
Mean	29.9	32.7	32.1	29.2	32.8	9.7	9.6	4.7
Standard error	2.1	2.3	2.3	2.2	2.5	0.5	0.5	0.3
Median	17	19	18	15	16.15	9.85	9.63	3.4
Mode	0	0	0	0	0	21.8	0.27	1.49
Standard deviation	35.48	38.56	39.29	37.35	41.90	9.16	8.89	5.37
Kurtosis	1.46	1.00	1.14	2.69	1.27	-1.30	-1.38	16.58
Skewness	1.38	1.26	1.32	1.58	1.41	-0.05	-0.01	3.14
Minimum	0	0	0	0	0	-8.3	-6.9	0.01
Maximum	167	181	194	201	174.5	25.4	24	47.47

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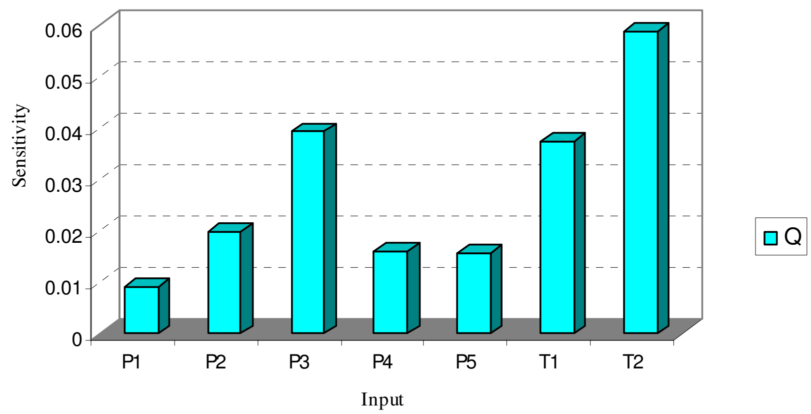

Figure 2. Sensitivity of output (discharge) to input (rainfall and temperature).

Table 2. MSE and NMSE for different hidden layers.

Hidden layer	1	2	3	4	5
MSE	11.6	11.8	12.9	26.6	133.1
NMSE	2.06	2.1	2.29	4.73	23.64

RESULTS

Preprocessing of data was done. Table 1 represents some statistics of the monthly observed data. Mean monthly rainfall in selected stations varied from 29.2 to 32.8 millimeters. Temperature ranging from 9.6 to 9.7^{o}C denotes a lower deviation as compared to rainfall.

Multilayer Perceptron

Several topologies for MLP were examined. Sensitivity analyses for created networks were tested. The results of the sensitivity analysis are presented in Figure 2. Learning rate changes from 0.01 to 0.1, momentum rule was used for increasing convergence from 0.4 to 1. The process was iterated 2000 times. Learning rate equal to 0.05 and momentum equal to 0.8 showed the best results. The increase in the hidden layers resulted in increase of errors. Table 2 represents MSE and NMSE for different hidden layers. Suitable PE was determined as 4. Finally the suitable structure was determined as 7.4.1. In some cases, the learning curve was found as unstable, so the process was repeated to achieve optimum learning curve. Learning curves for selected structures are presented in Figure 3.

Regarding the appropriate topology and parameters, testing step was run. Results for three stages are shown in Figures 4 to 6.

Recurrent Neural Networks

In the next stage of this study several topologies for time lagged recurrent network were created and compared as with errors. Memories of Gamma axon, Laguarre axon and TDNN axon were used for corporation. TDNN axon memory tends to result in the best. The depth of axon and trajectory length were changed to obtain the optimum. Learning rate, momentum and epoch respectively

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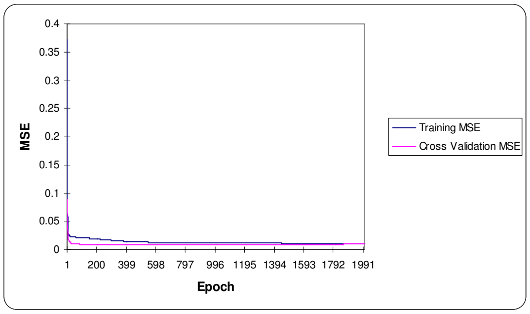

Figure 3. Learning curve for selected topology.

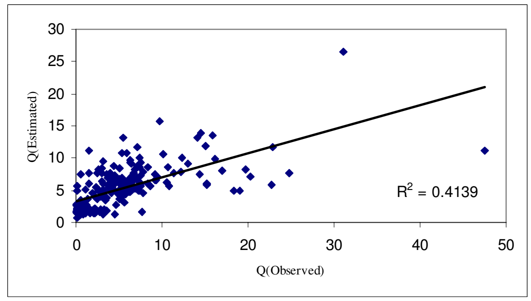

Figure 4. Plot of observed and estimated discharge ($m^3\ s^{-1}$) for training.

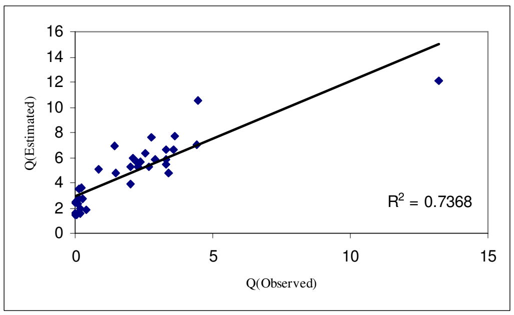

Figure 5. Plot of observed and estimated discharge ($m^3\ s^{-1}$) for testing.

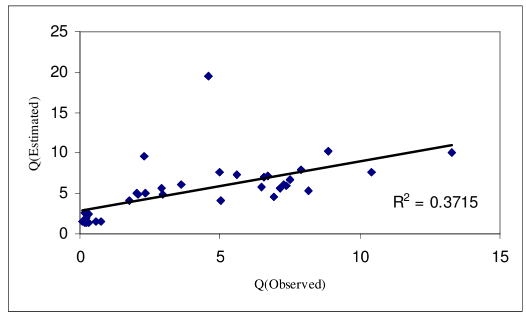

Figure 6. Plot of observed and estimated discharge ($m^3\ s^{-1}$) for CV.

Table 3. Errors for different hidden layers in TLRN networks.

Hidden layer	1	2	3	4	5
MSE	4.91	8.48	14.19	35.69	37.98
NMSE	0.87	1.51	2.52	6.34	6.74

equal to 0.1, 0.7 and 2000, were considered. Suitable selected topology was 7.4.1. More than 1 hidden layer resulted in more error (Table 3).

Learning curve for suitable topology is shown in Figure 7. With regard to best topology and parameters, testing set was conducted. Results for three sets are shown in Figures 8 to 10.

Errors of three sets of MLP and TLRN for the best topology and parameters are presented in Table 4.

DISCUSSION

The applicability and potential of ANNs including MLP and RNN for monthly runoff estimation was studied for Pelasjan River basin in Isfahan Province. Model performance was assessed through MSE, NMSE as well as correlation coefficient. Sensitivity analysis suggests that all inputs have significant effects on output among which monthly temperature is of the most effect. Input of P_3, located on the upland of studied basin has the maximum effect on output as compared with other rain gauge stations. Maximum and minimum rates of SA are related to T_2 and P_1, respectively. Using rainfall as the single input resulted in a weak estimation. Since there was no recommended rule for designing an ANN, different topologies were

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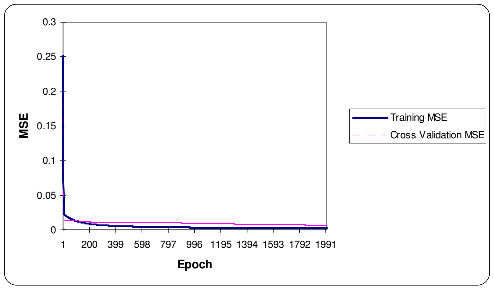

Figure 7. Learning curves for selected topology.

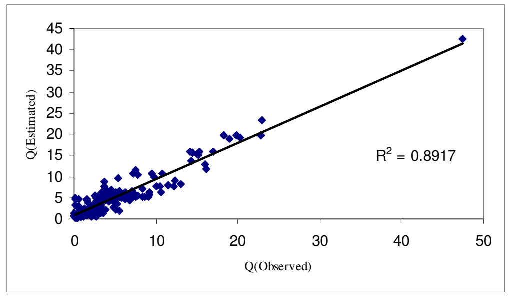

Figure 8. Plot of observed and estimated discharge ($m^3\ s^{-1}$) for training.

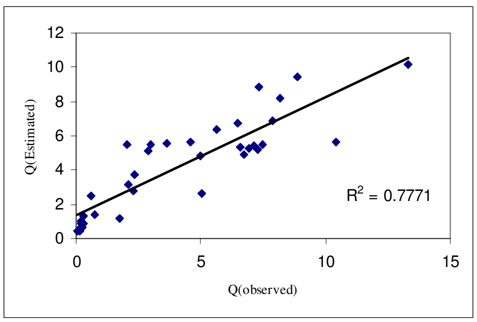

Figure 9. Plot of observed and estimated discharge ($m^3\ s^{-1}$) for CV.

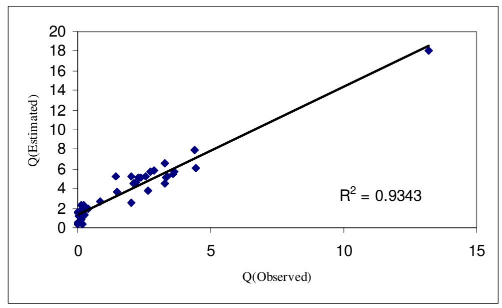

Figure 10. Plot of observed and estimated discharge ($m^3\ s^{-1}$) for testing.

created in the process.

MLP with one hidden layer and 4 perceptron elements a minimum error. However the effects of temperature inputs are significant in achieving better learning. Activation functions of hyperbolic tangent and sigmoid were compared. Results imply that using hyperbolic tangent leads to better results, while the use of sigmoid function learning process being consistent. In each network in order, to avoid overtraining, cross validation was employed as the criterion. In general, running 2,000 iterations tends to depict appropriate results. The training set was repeated for new architectures. In TLRn a topology of 7.6.1 was selected. Training set in TLRn is more difficult than in MLP networks, the learning process is very sensitive, the probability occurrence of local minima being more. To eliminate this problem, training was repeated frequently. In each network with increasing hidden layer, training was unstable and error increased. With regard to Figure 5, it is evident that a plot of observed and estimated discharge is depicted with much deviation from the fitting line. This deviation is more for the CV stages with r^2= 0.3715 showing a weak fitting of data. Learning curves in Figure 3 indicated that with increase in iterations, the error decreased showing a steady trend after 200 iterations in the CV stage. Learning curves in the TRNN were more stable than those in MLP showing less errors. These curves for test and CV sets followed similar patterns. But the error in CV stage increased following 200 iterations showing a little more errors than the test stage. Scatter plots in the TRNN represented better results as compared with the MLP. In the TRNN, data was fitted around the fitting line, with a suitability of r^2=0.93 in CV stage.

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Table 4. Errors of two types of ANNs for the best topology.

NN	MLP			TLRN		
Error criteria	Training	Cross validation	Testing	Training	Cross validation	Testing
MSE	19.94	11.06	9.27	3.23	2.79	4.91
NMSE	0.59	0.92	1.65	0.11	0.23	0.87
r	0.64	0.61	0.86	0.94	0.88	0.97

Results indicated that errors in TLRN are less than those in MLP networks. Correlation coefficient in MLP networks was 0.64 in training, 0.61 in cross validation and 0.86 in testing set but in TLRN these reached 0.94 in training, 0.88 in cross validation and 0.97 in testing set. The monthly runoff in the study area contains the extra amount of flow due to the slow response of the previous month's rainfall. For the rainfall-runoff process where both the input and output are temporal variables, static networks have been criticized even with the inclusion of input from previous months. In this sense recurrent networks are more suitable for the rainfall-runoff problems in comparison with MLP networks. Also determining optimal network architecture was found to be critical for efficient mapping of the rainfall-runoff relationship. However ANNs especially the recurrent network can simulate monthly rainfall-runoff processes, effectively. Also these networks are capable of distinguishing the response of a basin to rainfall.

In summary, the recurrent networks are of a high capability of simulating runoff generation because of former knowledge of data being used in their structures for on optimal responses a diminishing of the error. In fact, runoff data is affected by previous data, this problem being intensified in mountainous regions where snowmelt contributes to surface flows.

REFERENCES

1. Bazartseren, B., Hildebrandt, G. and Holz, K. P. 2002. *Hydroinformatic Web Application and Web Service for Real-time Water Level Prediction and Short-Term Prediction*. Cottbus, Germany.
2. Bhattacharya, B., Lobbrecht, A. H. and Solomatine, D. P. 2003. Neural Networks and Reinforcement Learning in Control of Water System. *J. Water Resour. Planning Manage.,* **129(6)**:1-8.
3. Campolo, M., Andreussi, P. and Soltani, A. 1999. River Flood Forecasting with a Neural Network Model. *Water Resour. Res.*, **35(4)**:1191-1197.
4. Coulibaly, P., Anctil, F., Aravena, R. and Bobee, B. 2001. Artificial Neural Networks Modeling of Water Table Depth Fluctuations. *Water Resour. Res.*, **37(4)**:885-896.
5. Drecourt, J. P. 1999. *Application of Neural Network and Genetic Programming to Rainfall-Runoff Modeling*. D2K Technical Report, Danish Hydraulic Institute.
6. French, M. N., Krajewski, W. F. and Cuykendall, R. R. 1992. Rainfall Forecasting in Space and Time Using a Neural Network. *J. Hydrol.,* Elsevier Science Publication, **137**: 1-31.
7. Gorindaraju, R. S. and Rao, A. R. 2000. *Artificial Neural Networks in Hydrology*. Klumar Academic Publishers, Netherlands, Water Science and Technology Library.
8. Govindaraju, R. S. 2000. Artificial Neural Networks in Hydrology: II, Hydrologic Applications. *J. Hydrol. Eng.,* **5(2)**: 124-137.
9. Jagadeesh, A., Zhang, B. and Govindaraju, R. 2000. Comparison of ANNs and Empirical Approaches for Predicting Watershed Runoff. *J. Water Resour. Planning Manage.,* **126(3)**:156-166.
10. Kingstone, G. B., Lambert, M. F. and Maier, H. R. 2004. *Development of Stochastic Artificial Neural Networks for Hydrological Prediction*. Center for Applied Modeling in Water Engineering, University of Adelaide, Australia.
11. Kisi, O. 2005. Daily River Flow Forecasting Using Artificial Neural Networks and Auto-Regressive Models. *Turkish J. Eng. Envir. Sci.,* **29**:9-20.

[Downloaded from jast.modares.ac.ir on 2025-01-14]
[DOR: 20.1001.1.16807073.2009.11.3.4.7]

12. Kumar, D. N., Rajo, K. S. and Satish, T. 2004. River Flow Forecasting Using Recurrent Neural Networks. *Water Resour. Manage.,* **18**: 143-161.
13. Madson, H., Butts, M. B., Khu, S. T. and Liong, S.Y. 2000. Data Simulation in Rainfall-Runoff Forecasting. Hydroinformatics 2000, 4th International *Conference on Hydro informatics*, Iowa, USA.
14. Mahnaj, M. 2002. *Neural Networks (Computational Intelligence)*. Vol.1, 2nd Ed., Amirkabir Technology University Publications, Tehran.
15. Maier, H. R. and Dandy, G. C. 2000. Neural Networks for the Prediction and Forecasting of Water Resources Variable: A Review of Modeling Issues and Application. *Environmental Modeling and Software,* **5**: 101-124.
16. Singh, V. P. and Woolhiser, D. A. 2002. Mathematical Modeling of Watershed Hydrology. *J. Hydrol. Eng.,* **7(4)**: 270:292.
17. Vladan, B. and Christian, L. 1998. *Hydroinformatics'98*. Vol. 2, Rotterdam, Netherlands.
18. Yazdani, M. R. and Chavoshi, S. 2005. River Flow Forecasting Using Artificial Neural Networks. 5th Iranian *Conference on Hydraulics*, Kerman, Iran. 911-918.

تخمین رواناب ماهانه با استفاده از شبکه‌های عصبی مصنوعی

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چکیده

یکی از مهمترین چالشها در مدیریت آب و آبخیزداری تخمین رواناب می باشد. تغییرات زمانی و مکانی فاکتورهای شکل‌دهنده رواناب که ناشی از ناهمگنی در حوضه آبخیز می باشد، سبب پیچیدگی روابط شده است. از جمله تکنیکهای هوش مصنوعی شبکه‌های عصبی مصنوعی می‌باشد که دارای انعطاف‌پذیری بوده و نیازمند شرایط پیچیده فیزیکی نیست. این شبکه‌ها قادر به تعیین روابط ورودی و خروجی می‌باشند. در این تحقیق دو مدل از شبکه عصبی مصنوعی برای تخمین رواناب ماهانه حوضه رودخانه پلاسجان در بخش مرکزی ایران مورد بررسی قرار گرفت. مدلهای استفاده شده شامل پرسپترون چند لایه و شبکه‌های عصبی برگشتی یا چرخشی می‌باشد. ورودیهای مدل شامل اطلاعات مربوط به ۵ ایستگاه بارانسنجی و دو ایستگاه دمانگار و خروجی مدل جریان ماهانه در ایستگاه هیدرومتری اسکندری می‌باشد. پیش پردازش داده‌ها و آنالیز حساسیت بر روی داده‌ها انجام گرفت. توپولوژی‌های گوناگونی از شبکه‌های عصبی با تغییر در لایه های ورودی، گره‌ها و لایه‌های مخفی ایجاد شد. بهترین ساختار ۷,۴,۱ تعیین گردید. نتایج بیانگر این بود که شبکه‌های عصبی برگشتی نتایج بهتری از پرسپترون چند لایه در تخمین رواناب در حوضه مورد مطالعه دارند. همچنین برای تخمین رواناب، شبکه‌های عصبی مصنوعی قادرند رفتار حوزه را نسبت به بارش در حوزه بخوبی نشان دهند.

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