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Runoff Simulation and Prediction through using Basic Data Models

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ABSTRACT
Accurate prediction of river flow plays a leading role in water resources planning. The experts always seek for new tools to enhance prediction accuracy of rivers' flow. Regression models, time series, and artificial intelligence are common hydrological prediction methods. As modeling nonlinear relations, artificial intelligence methods are more popular than other methods. Thus, present research uses two artificial intelligence methods including Artificial Neural Network (ANN) and Support Vector Regression (SVR) to predict Saeid Abbad river flow located in East Azerbaijan. Results are compared according to explanation coefficient statistics (R^2), root mean square error (RMSE), and volume error (VE) mean. Findings show that R^2, RMSE, and VE values of SVR model are 0.8, 0.196, and 0.052, respectively. Similarly, the values are 0.638, 0.153, and 0.154, respectively, for ANN model indicating SVR outperforms ANN.
Key words: *Flow prediction, Saeid Abbad River, support vector regression, artificial neural network.*

INTRODUCTION

In recent decades, increased water demand resulting from increasingly higher human population, on one hand, and limited water resources, on the other hand, led to considering the need of proper and efficient use of water resources. Exact flow prediction in rivers is one of the most important basics of surface water resources' management. Predictions, in particular long-term predictions, are useful in most parts of water resources management such as agriculture planning, environmental protection, drought management, required utilities, and reserve optimal utilization. Prediction is principally performed based on regression models. Such models fit a relation between input and output data in terms of existed information in order to estimate the appropriate output value for new entries. Univariate or multivariate regression equations and auto regressive models are the simplest ones. Developing artificial intelligence and machine learning, in recent years, has increasingly led to applying new approaches such as artificial neural networks (ANN) and support vector machine (SVM) in regression issues.

Many studies were conducted in this area, for instance, Fattahie *et al* [1] predicted stream flow through using artificial neural network (ANN). They applied climate signals in predictions and results showed that signals usages cause models' improved performances. Naveh *et al* [2] predicted stream flows of Barandouz Chai and Shahre Chai Rivers, Uremia, by using nonlinear time series models. Results demonstrate that nonlinear model is more capable in predicting flow than linear models. Azmi and Araghi Nejad [3] predicted upstream flow of Zayande Roud using nearest neighbor approach. Results show that selecting five neighbors can lead to appropriate conclusions. Abdollahi Asad Abadi *et al* [4] studied daily mean discharge forecasting of Behesht Abad river by using ANN and wavelet analysis. Results show that using wavelet analysis causes improving models' performances. Bagheri Niya and Borhani Daryan [5] evaluated several flows forecasting models and concluded that using rainfall simultaneously with predictor variable can improve results up to 16-55%. Schär *et al* [6] forecasted seasonal flow of a river in Swiss. Sedki *et al* [7] simulated daily flow through ANN. He trained ANN by using genetic algorithm (GA) and compared results to post-propagation training algorithm. Findings reveal that network training through GA provides better results. Cannas *et al* [8] applied ANN and wavelet analysis in predicting river basin flow of Sardinia River, Italy. Results demonstrate that applied model preciously forecasts flow discharge. Wang *et al* [9] comprehensively compared artificial intelligence approaches in runoff predictions through using ANN, SVM, Adaptive- Neural Fuzzy Inference Systems (ANFIS), as well as Genetic planning. The results indicated ANFIS, GP, and SVEM outperformance.

As significance of properly predicting river flows in water resource, planning and its critical role in water resource management, this research studies two artificial intelligence approaches in forecasting Saeid Abaad river discharge, East Azerbaijan. Support vector regression and artificial neural network methods were used. Both models' results were compared following monthly river flow forecasting and models' advantages and disadvantages were provided.

METHODS AND MATERIAL

Artificial neural network (ANN)

In recent decades, using artificial neural networks (ANN) are common in regression models such that it can be stated that it is now regarded as the most prevalent forecasting approach. There are several artificial neural networks like well-known Multi-layer Perceptron neural network (MLP). It consists of an input layer, one or more intermediate (hidden) layers, as well as an output layer. Activation function is usually sigmoid and linear in hidden and output layers, respectively. Findings of several studies reveal that a hidden layer can accurately estimate any complex function; hence, neuron numbers in the middle layer is the only regulatory parameter, which is determined through trial and error method. Each network has one or more independent variable (input variable) summed by a linear function in output layer followed by passing intermediate layer neurons, results in an output. In this study, MLP inputs are flow discharge and rainfall of previous months and the amount of flow in next month is network output.

Support vector regression

Support vector regression (SVR) was introduced by Vapnik in 1995 [10]. It minimizes operational risk instead of minimizing least error in MLP. It means that an equation is selected among all estimating equations with the same error such that error is minimal in the case of new entries. Estimation in SVR is performed in a range in which determining that range requires finding support vectors. These support vectors result from solving a quadratic planning. Kernel function used in SVR can be of different functions; however, the widely common kernel function is Radial Basis Function. This function is extensively applied as its adequate efficiency (see Vapnik [10] for more details).

Case study

This research studied monthly flow forecast at Saeid Abaad hydrometric station site within water years of 1970-71to 2007-2008 since its data relative sufficiency and adequate statistical quality. This site is located in Uremia lake basin and sub-basin of Aji Chai at 46 ° and 18 min eastern longitude and 37° and 54 min northern latitude. Aji Chai sub-basin is situated in the east of Uremia Lake and is considered the second largest sub-basin of Uremia lake sub-basins. Saeid Abbad River located in central areas and Oskou, Tabriz is a branch of Aji Chai River. According to runoff data calculation and 38-year registered rainfall at Saeid Abaad hydrometric station, Saeid Abaad River average discharge and average rainfall are annually 9.4 mm^3 and 384.3 mm, respectively.

Prediction model

Several models are considered for forecasting runoff using studied methods. Rainfall and river flow in previous months and discharge amount regard as input and output, respectively. The models are as follows:

$$Q_{t+1} = f(Q_t, P_t) \quad)1($$

$$Q_{t+1} = f(Q_t, Q_{t-1}, P_t, P_{t-1}) \quad)2($$

$$Q_{t+1} = f(Q_t, Q_{t-1}, Q_{t-2}) \quad)3($$

$$Q_{t+1} = f(Q_t, Q_{t-1}, Q_{t-2}, P_t, P_{t-1}, P_{t-2}) \quad)4($$

Where Q is flow discharge, P is rainfall Precipitation, and t indicates time.

Evaluation criteria

There are three criteria including correlation coefficient (R), Root Mean Square Error (RMSE), as well as Mean Absolute Error (VE) for models assessment and results comparison. The criteria are defined as follows:

$$R = \frac{\frac{1}{n}\sum_{i=1}^{n}(O_i - \overline{O})(f_i - \overline{f})}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - \overline{O})^2}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - \overline{f})^2}} \quad)5($$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - f_i)^2} \qquad)6($$

$$VE = \frac{1}{n} \sum_{i}^{n} \left| \frac{o_i - f_i}{o_i} \right| \times 100 \qquad)7($$

Where, Q_i is observed values at i^{th} time step; f_i is the predicted values at i^{th} time step; $\bar{O}$ shows mean observed values; $\bar{f}$ is the predicted mean values; and n is data number. The model is more favored as higher R, less RMSE and VE.

RESULTS

Prepared information of several models divides into two training and experimental sections (75% for training and 25% for experimental). Flow discharge was forecasted by using both models through two MLP and SVR approaches, findings demonstrate that model 4 (equation 4) has the best results. Thus, model 4 results are studied in the following. According to obtained results, both MLP and SVR approaches possess adequate accuracy. Both methods had similar performances in term of efficacy criteria including R, RMSE, and VE. MLP's R-value obtained 0.797 in training step; while, R in SVR slightly improved to 0.8. The methods also similarly performed in experimental step such that RMSE value related to MLP and SVR obtained 0.152 and 0.153, respectively. Other results are shown in Table 1.

Table 1- Obtained evaluation criteria of both methods in training and experimental stages

	Training			Experimental		
	R	RMSE	VE	R	RMSE	VE
MLP	0.797	0.199	0.066	0.627	0.152	0.182
SVR	0.800	0.196	0.052	0.638	0.153	0.154

Figure 1 of training data shows flow simulated value through the two aforementioned methods. Flow forecasted values of experimental data are seen in Figure 2. Both methods appropriately forecasted runoff value regarding Fig.1; whereas, in maximum values lacked proper performance and estimated less than flow real discharge value. This value is more pronounced in SVR approach indicating that SVR estimations are weaker that MLP in assessing current maximum discharges in time series; however, both SVR and MLP approaches well performed in estimating minimum and mean flow values. Methods' performance slightly decreased in testing performance; while, estimating maximum values was much accurate comparing training phase as large maximum values such as training information among existed information. River flow was low at the beginning of training period, which was likely due to draught. Both MLP and SVR having best estimations overestimated discharge value.

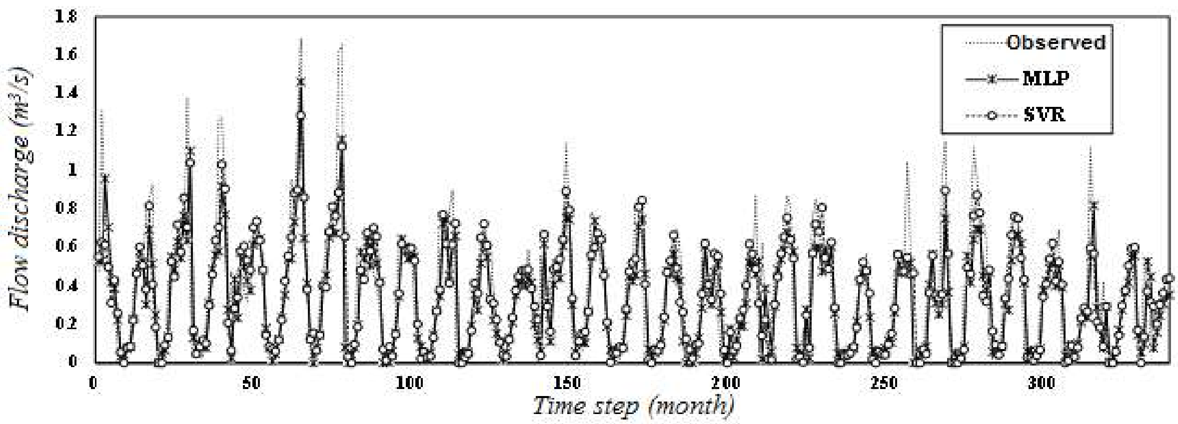

Fig 1. Observed and forecasted values of discharge in Saied Abaad station at training level

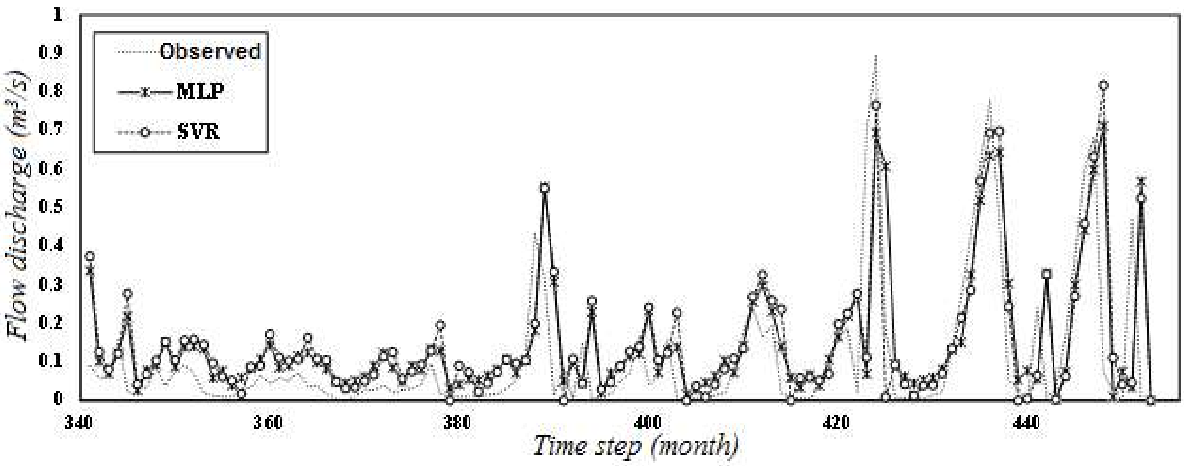

Fig 2. Observed and forecasted discharge values in Saeid Abaad station at experimental phase

CONCLUSION

The goal of this research was comparing two artificial intelligence methods in predicting river flow. Thus, data of rainfall and flow discharge of Saeid Abaad hydrometric station within 1970-71 to 2007-08 water years. Flow was forecasted by using MLP neural network and SVR methods. Results revealed that maximum discharges values of training step were underestimated in both methods in comparison to observed values; whereas, both performed well in assessing normal and minimum values. Minimum discharges were almost estimated more than observed values at experimental phase; however, maximum values were appropriately predicted. Studying and comparing results in terms of three R, RMSE, and VE criteria demonstrated that both methods have almost similar accuracy; however, SVR method, in general, outperforms.

REFERENCES

1. Fattahi, A., Delavar, M., and Nouhie, K. (2012). *Forecasting flow of Northern Karoun Rivers through artificial neural networks.* Geographical research quarterly, 27(1), 17819-17847.
2. Naveh, H., Khalili, K., Taghi Alami, M., and Behmanesh, J. (2012). *Forecasting river flow through nonlinear two-linear time series (Case study: Barandouz Chai and Shahr Chai Rivers, Uremia).* Soil and Water publication, 26 (5): 1299-1307.
3. Azmi, M., Araghi Nejad, Sh. (2012). *Developing K-regression method- nearest neighbor in forecasting river flow.* Water and waste water, 2, 107-118.
4. Abdullahi Asad Abaadi, S., Din Pajouh, Y., and Mir Abbasi Najaf Abaadi, R. (2013). *Forecasting daily mean discharge of Behesht Abaad River through wavelet analysis.* Water and soil publication, 28(3): 534-535.
5. Bagheri Niya, M., and Borhani Daryan, A. (2013). *Evaluating river flow forecasting models.* Journal of Irrigation and Water Engineering 4(13): 14-30.
6. Schär, C., Vasilina, L., Pertziger, F., andDirren, S. (2004). *Seasonal runoff forecasting using precipitation from meteorological data assimilation systems.*Journal of Hydrometeorology, 5(5), 959-973.
7. Sedki, A., Ouazar, D., and El Mazoudi, E. (2009). *Evolving neural network using real coded genetic algorithm for daily rainfall–runoff forecasting.* Expert Systems with Applications, 36(3), 4523-4527.
8. Cannas, B., Fanni, A., Tronci, S., andZedda, M. K. (2005). *River flow forecasting using neural networks and wavelet analysis.* In Geophysical Research Abstracts (Vol. 7, p. 08651).
9. Wang, W. C., Chau, K. W., Cheng, C. T., andQiu, L. (2009). *A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series.* Journal of hydrology, 374(3), 294-306.
10. Vapnik, V., (1995). *The Nature of Statistical Learning Theory.* Springer Verlag, New York, USA.