تحقیقات منابع آب ایران
Iran-Water Resources Research

سال پنجم، شماره ۳، زمستان ۱۳۸۸
Volume 5, No. 3, Winter 2010 (IR-WRR)
4-7

*Extended Abstract*

# Uncertainty Analysis of Artificial Neural Networks and Neuro-Fuzzy Models in River Flow Forecasting

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## Introduction

Streamflow forecasts are of great importance in water resources management. However, due to the high uncertainty in the rainfall-runoff simulation procedure, forecasts are usually problematic. Uncertainty analysis is traditionally applied for streamflow forecasts using statistical approaches. But data-driven models like the Artificial Neural Network (ANN) and the Adaptive Network Fuzzy Inference System (ANFIS) have been rarely considered. The objective of this paper is to determine the uncertainty associated with ANN and ANFIS models for 1 to 3 months lead time forecasts and compare these models in this regard. To explore the methodology, Sofy-chai river at Tazkand station in north-western Iran is selected.

## Methodology

Considering the complexity and influence of uncertain factors on river discharges, there is a strong need to present solutions to define the relationship between the input and output data skipping a complete and complex physical understanding of the system. Data-driven models are good candidates for such analyses (Nayak et al., 2005). Two types of this paradigm in modeling are ANNs and ANFIS that have recently gained popularity as emerging and challenging computational techniques. Furthermore, they offer advantages over conventional modeling, including the ability to handle large amounts of noisy data from dynamic and nonlinear systems, better performance, faster model development, and less calculation times (Aqil et al, 2007). ANN is inspired by neurobiology to perform brain-like computation. Network structure consists of a number of nodes connected through directional links. Each node represents a process unit and each link specifies a causal relationship between nodes (Jang et al., 1997). The neuro-fuzzy approach combines the advantages of fuzzy logic (Zadeh, 1965) and ANN and designs an architecture that uses a fuzzy logic to represent knowledge in an interpretable manner and the learning ability of a neural network to optimize its parameters (Jang and Gulley, 1995).

One of the important subjects that have rarely been considered for application of these models is incorporating uncertainty. It is obvious that the forecasts are not fully certain and such an analysis can result in more operational application of these models. Review of the literature showed that this subject has been considered to some extent in the research work of Marce et al. (2004). This calculation is based on implementing the models in a Monte Carlo framework. Monte Carlo simulation involves repeatedly forming a random vector of parameters from prescribed probability distributions, evaluating the function, and then computing the statistics of the evaluated function.

## Results and Discussion

Considering the snowy regime of the Sofy-chay river, all of the available data are contributing in choosing the best inputs of the forecast models. The analysis showed that the discharge and the maximum temperature with two lags are the best input combination for 1 to 3 month forecasts. In this manner, the forecasting models are defined as:

$$Q(t+n) = f\left[Q(t), Q(t-1), T_{max}(t), T_{max}(t-1)\right]$$
$$n = 1,2,3$$

where $n$ is the forecasting lead time, Q is the discharges, and T is the temperature.

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The first 14 years of observed data and the remaining 4 years are used for model calibration and validation, respectively. Models performance in calibration and validation periods are evaluated using the correlation statistic (R), the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE). To indicate the uncertainty of the final models 1000 iterations of the Monte Carlo simulation were applied. In each iteration 10 years out of 14 years of calibration period are randomly selected for training of the models and the remaining 4 years are applied for supervising the learning process. The calculations resulted 1000 outputs for each month.

Using a simple statistical analysis, the 95% confidence interval of the models output were determined. To compare the models regarding the uncertainty, the bandwidth factor (d-factor) and the 95 percent prediction uncertainty (95PPU) indices were used. The performance indices of the forecasted streamflows for 1 to 3 months lead time from individual models and the average of 1000 iterations are presented in Table 1. The uncertainty indices of the models are shown in Table 2. Also, Figure 1 shows the 95% confidence interval of the ANN and ANFIS model outputs for 1 to 3 month forecasts.

As shown in Figure 1, ANN has shown higher uncertainty for all forecasts. However, it can be seen that inspite of its wider confidence band the percentage of the observed data that rest on the band was not significantly higher than ANFIS. It is also observed that the ANN was more sensitive to the training data and even for the low flows that usually face lower uncertainty, an improper band was resulted. Meanwhile, ANFIS provided a smaller confidence band and accordingly less observed data within. But, the uncertainty of this model, especially for low flows was more realistic.

**Table 1- Performance indices of the ANN and ANFIS models for 1 to 3 month forecasts**

| Lead Time | Performance Index | Mean of 1000 Iteration outputs | | | | Individual Models Output | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | ANN | | ANFIS | | ANN | | ANFIS | |
| | | Calibration | Validation | Calibration | Validation | Calibration | Validation | Calibration | Validation |
| 1 Month Ahead | *R* | 0.93 | 0.9 | 0.95 | 0.9 | 0.91 | 0.89 | 0.9 | 0.88 |
| | *MAE* | 1.02 | 1.03 | 0.89 | 1.03 | 1.1 | 1.12 | 0.99 | 1.11 |
| | *RMSE* | 1.71 | 1.68 | 1.44 | 1.78 | 1.77 | 1.89 | 1.66 | 1.93 |
| | *MAPE* | 46.07 | 49.77 | 34.46 | 36.02 | 49.85 | 54.24 | 32.95 | 38.22 |
| 2 Month Ahead | *R* | 0.82 | 0.84 | 0.87 | 0.88 | 0.81 | 0.8 | 0.87 | 0.82 |
| | *MAE* | 1.56 | 1.25 | 1.35 | 1.01 | 1.55 | 1.3 | 1.44 | 1.17 |
| | *RMSE* | 2.67 | 2.13 | 2.34 | 1.86 | 2.61 | 2.25 | 2.51 | 2.01 |
| | *MAPE* | 63.21 | 60.98 | 45.75 | 39.18 | 63.76 | 65.24 | 50.32 | 44.57 |
| 3 Month Ahead | *R* | 0.88 | 0.84 | 0.91 | 0.87 | 0.85 | 0.78 | 0.83 | 0.79 |
| | *MAE* | 1.29 | 1.3 | 1.1 | 1.2 | 1.34 | 1.39 | 1.19 | 1.37 |
| | *RMSE* | 2.23 | 2.18 | 1.9 | 2.01 | 2.32 | 2.31 | 2.04 | 2.24 |
| | *MAPE* | 47.73 | 53.21 | 33.71 | 45.59 | 55.76 | 58.68 | 40.42 | 49.71 |

**Table 2- Uncertainty indices of the ANN and ANFIS models for 1 to 3 month forecasts**

| Lead Time | Uncertainty Index | ANN | | ANFIS | |
|---|---|---|---|---|---|
| | | Calibration | Validation | Calibration | Validation |
| 1 Month Ahead | *d-factor* | 0.86 | 0.93 | 0.48 | 0.63 |
| | *95PPU (%)* | 81.06 | 79.16 | 73.96 | 77.08 |
| 2 Months Ahead | *d-factor* | 0.85 | 0.92 | 0.59 | 0.68 |
| | *95PPU (%)* | 73.96 | 72.91 | 70.41 | 70.83 |
| 3 Months Ahead | *d-factor* | 0.69 | 0.71 | 0.57 | 0.62 |
| | *95PPU (%)* | 76.33 | 75.00 | 71.60 | 62.50 |

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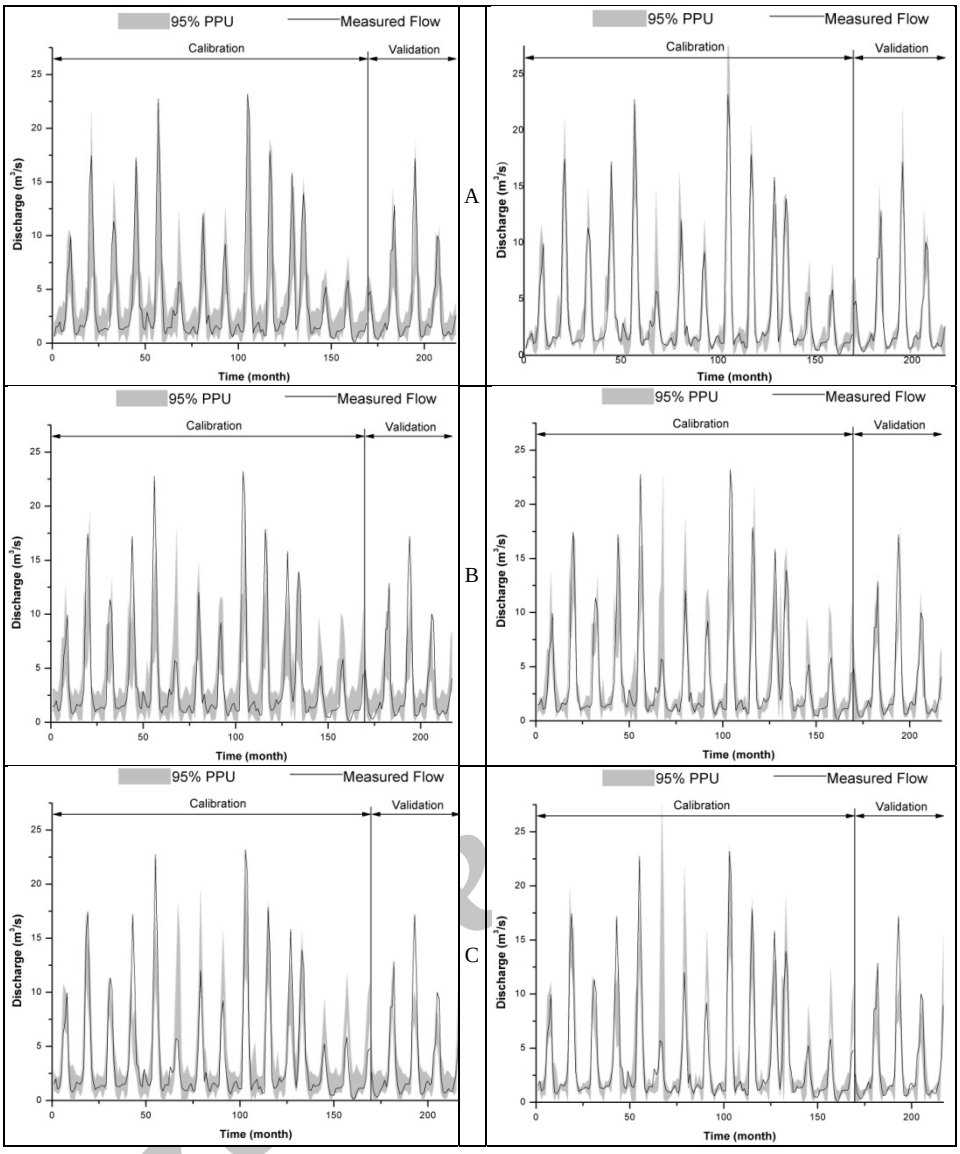


**Figure 1- Observed flows and 95% confidence interval of ANN (left) and ANFIS (right) models, (A) 1 month ahead, (B) 2 months ahead and (C) 3 months ahead.**

## Conclusion

Comparison of the ANN and ANFIS models showed that ANFIS was associated with lower uncertainty and better performance in the forecasts. Also, the results showed that the uncertainty increases during high flows. This can be due to the higher complexity of rainfall-runoff process in such conditions which exclude some effective factors due to lack of information.

The applied methodology could satisfactory incorporate uncertainty analysis in the ANN and ANFIS models and it can be applied for other research It is also very useful for operational purposes such that the decisions can be taken with considering the associated risk.

***Keywords*:** River Flow Forecasting, Uncertainty, Artificial Neural Network, Neuro-Fuzzy.

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