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EXTENDED ABSTRACT

Estimation of Prediction Intervals for ANN- Based Rainfall- Runoff Modeling

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1. Introduction

In this study, Lower Upper Bound Estimation (LUBE) method, which was firstly introduced by Khosravi et al. (2010) and is a novel PIs construction method in hydrologic issues, is applied to construct PIs for ANN-based rainfall-runoff modeling. This technique is independent of any knowledge about the bounds of PIs or data distribution. The ANN-based LUBE method includes two outputs showing upper and lower bounds of prediction in contrast to the classic ANNs, which consider one output as point prediction. In this way, dominant input data combination is selected by the mutual information (MI) to the model rainfall-runoff process in both monthly and daily scales for two different watersheds in Iran and USA. Finally, the obtained PIs by the proposed LUBE method are compared with those obtained by the classic Bootstrap method.

2. Methodology

2.1. Study area and data set

In this paper, the data from two watersheds with various geomorphology were considered for the modeling, West Nishnabotna River (a sub-basin of Missouri River in the United States) and Lighvanchai River (a sub-basin in Iran). The first set of data used in this paper is for the Lighvanchai watershed located in northwest Iran at Azerbaijan province. The time series data was obtained from Iran Water & Power Resources Development Co. (IWPC) for the Lighvan station. This watershed is one of the main sub-tributaries of the Ajichai River, which discharges to Urmia Lake. Lighvanchai watershed is located between 37° 43′ and 37°50′ North latitude and 46°22′ and 46°28′ East longitude in the northern slope of Sahand Mountain (northwestern Iran). The watershed area is approximately 142 km^2. The second study area, the West Nishnabotna River watershed, is the main sub-basin of the Missouri River watershed that is located in southwestern Iowa. The river is placed at the longitude and latitude coordinates of 95° 67′ W and 40° 51′ N and the longest stream length of this river is about 190 km in Randolph station. For the study period, monthly and daily data were extracted from the waterwatch.usgs.gov website.

2.2. PIs construction by LUBE method

The structure of ANN with two outputs for estimating upper and lower bounds of PIs via the LUBE method is shown in Fig. 1. The first output corresponds to the upper bound and the second stands for the lower bound. In the first step, the data set is split into training and validation subsets, then an ANN with two outputs (optionally for initial values of outputs, ±5% of observed values can be considered to train ANN and find initial guesses for the weights). Then weights are randomly perturbed around the initial weights to generate some

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new weight sets. Dhanesh and Sudhear (2011) have reported that ANN weights are sensitive in a range of ±10% from the calibrated values, therefore some new ANNs with the several sets of perturbed weights (in the range of ±10% around initialized weights) are created and ANNs are simulated with these weight sets to obtain different sets of PIs.

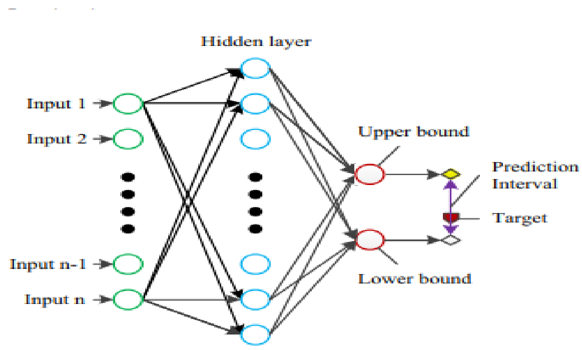

Fig. 1. ANN model for estimating upper and lower bounds of PIs (Quan et al. 2014)

2.3. PIs construction by Bootstrap method

Efron and Tibshirani (1993) developed the Bootstrap method, which resamples the training datasets for the purpose of generating various models by training an individual network on each resampled instance of the original dataset. The positive point about the application of this technique is that it does not require complex derivatives of any non-linear function.

3. Results and discussion

3.1. Results of point prediction by ANN model

Eight ANNs with different inputs were trained in this study on monthly and daily scales. The used time series as inputs of ANN were tabulated in Table 1. For calibration and validation of the ANNs, the data set was split into two parts, 75% of the data were used to train and the rest 25% were used to validate. Therefore, the data in periods 1981-2007 and 1987-2005 were used for the training, respectively for Lighvanchai and West Nishnabotna River and in periods 2007-2015 and 2005-2015 for the validation purpose. The obtained results of point prediction were tabulated in Table 1.

Table 1. Point prediction results for two watersheds in both daily and monthly scales

Scale	Basin	ANN	input	NSE train	NSE verification	R train	R verification	RMSE train	RMSE verification
Daily	Lighvanchai	1	I_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	0.81	0.72	0.9	0.84	0.007	0.01
		2	Q_{t-1}, Q_{t-2}, Q_{t-3}	0.93	0.9	0.96	0.95	0.02	0.03
	West Nishnabotna River	3	I_t, Q_{t-1}, Q_{t-2}	0.56	0.54	0.75	0.75	0.02	0.03
		4	Q_{t-1}, Q_{t-2}, Q_{t-3} Q_{t-4}, Q_{t-5}	0.7	0.7	0.84	0.83	0.02	0.03
Monthly	Lighvanchai	5	I_{t-1}, Q_{t-1}, Q_{t-2}	0.71	0.64	0.84	0.8	0.07	0.08
		6	Q_{t-1}, Q_{t-2} Q_{t-3}, Q_{t-12}, Q_{t-13}	0.84	0.66	0.92	0.8	0.05	0.08
	West Nishnabotna River	7	I_{t-1}, Q_{t-1}, Q_{t-2}	0.55	0.5	0.67	0.69	0.08	0.1
		8	Q_{t-1}, Q_{t-2} Q_{t-12} Q_{t-13}	0.5	0.5	0.69	0.7	0.08	0.1

3.2. Results of PIs construction using LUBE and Bootstrap methods

The overall performance of any PIs construction method for ANN-based modeling depends on the network structure and training process. To obtain the most accurate results, the optimum number of neurons was determined by trial and error, and in this way, 1 to 12 numbers of neurons were checked by trial and error. The confidence level associated with all PIs was considered as 90%. Two criteria, PICP (Eq.1) and NMPIW (Eq. 2), were computed for each generated set of the weights (by perturbation of initialized weights) to find out the optimum structure of ANN for constructing the PIs (with a maximum value of PICP and minimum value of NMPIW). The obtained optimal PICP and NMPIW values in constructing the PIs are presented in Table 2.

$$PICP = \frac{1}{N}\sum_{i=1}^{N} c_i \qquad if \qquad L(X_i) < x_i < U(X_i) \rightarrow c_i = 1 \ ; else \ \rightarrow c_i = 0 \tag{1}$$

$$NMPIW = \frac{1}{Rn}\sum_{i=1}^{n} L(X_i) - U(X_i) \tag{2}$$

Table 2. Constructed PIs results for both watersheds via LUBE and Bootstrap methods

Scale	ANN model	LUBE		Bootstrap	
		PICP	NMPIW	PICP	NMPIW
daily	1	0.86	0.04	0.6	0.09
	2	0.93	0.25	0.89	0.11
	3	0.88	0.05	0.77	0.03
	4	0.74	0.04	0.72	0.02
Monthly	5	0.69	0.17	0.6	0.19
	6	0.56	0.1	0.83	0.3
	7	0.7	0.17	0.51	0.11
	8	0.73	0.14	0.75	0.18

4. Conclusions

In this paper, ANN-based modeling, for rainfall-runoff modeling for two watersheds of Lighvanchai and West Nishnabotna River, was carried out in monthly and daily time scales. The PIs of the predictions were constructed using the LUBE method, via an ANN with two outputs representing upper and lower bounds of the PIs. For quantitatively evaluating the performance of the constructed PIs, NMPIW and PICP criteria were computed for all models. The obtained results were then compared with the results of the classic Bootstrap method. Analysis indicated that daily scale modeling led to more reliable results in both PIs construction methods. Values of PICP, respectively, were up to 29% and 21%, higher in daily scale compared to monthly scale for constructed PIs of Lighvanchai and West Nishnabotna River basin modeling. It was concluded that the LUBE method could build narrow PIs with higher PICP, values of PICP and NMPIW respectively, for constructed PIs via LUBE method were up to 20% higher and 30% lower than those constructed via the Bootstrap method, which denoting to the superiority of LUBE method with regard to the Bootstrap method. Comparison between the performance of the two basins, indicated that Lighvanchai showed better performance compared to West Nishnabotna River basin, PICP values for constructed PIs of Lighvanchai basin modeling were up to 21% higher than those for West Nishnabotna River basion. The regular four seasons for the Lighvanchai basin causes the better performance of its modeling.

5. References

Efron B, Tibshirani RJ, "An introduction to the bootstrap", CRC press, 1994.

Khosravi A, Nahavandi S, Creighton D, "A prediction interval-based approach to determine optimal structures of neural network metamodels", Expert systems with applications, 2010, 37 (3), 2377-2387.

Quan H, Srinivasan D and Khosravi A, "Particle swarm optimization for construction of neural network-based prediction intervals", Neurocomputing, 2014, 127, 172-180.