Real-Time Short-Term Natural Water Inflows Forecasting Using Recurrent Neural Networks

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Abstract

Accurate, time and site-specific forecasts of natural inflows into hydropower reservoirs are highly important for operating and scheduling. Presently, available stochastic and conceptual models do not generally provide forecasts with accuracy appropriate for this task. This paper investigates the effectiveness of recurrent neural networks (RNN) for real-time short-term natural water inflows forecasting. The models use antecedent inflows and precipitation data, and actual weather descriptors to generate short-term (1-7 days ahead) natural inflow forecasts for a specific hydroelectric reservoir. The input variables are exactly the same as those previously used for an autoregressive moving average model with exogenous variables (ARMAX) and for a conceptual model (PREVIS). The RNN are trained using the early stopped training technique with the Levenberg-Marquardt Backpropagation (LMBP). The experimental results show that the performance of RNN using the early stopped training approach outperforms the traditional stochastic model and the available conceptual model. Particularly, the RNN have shown better forecasting capabilities for the last 3 of the seven days ahead forecasts.

Introduction

Like many of the activities associated with the planning and operation of a water resource system, hydropower reservoir management require forecasts of future events. For large hydropower systems, there are needs for accurate short-term forecasts of potential water inflows, in order to optimize reservoirs operation and scheduling. Different types of statistical and physical models have been proposed for this purpose [1] [2], but none of them can be considered as a single superior model. Owing to the complexity of hydrological processes such as rainfall-runoff and snowmelt, and the unknown impact of low-frequency climatic variability, there are many situations where accurate site-specific predictions remain a difficult task using classic autoregressive methods or even sophisticated physical-based models. As alternatives to the traditional stochastic models, hydrologists have recently resort to the artificial neural networks approach for hydrologic forecasting. Most of these experiments have focused on the three layer feed-forward network and the standard backpropagation (BP) algorithm [3]. Although standard BP training has proved to be efficient in some applications, its convergence tends to be very slow, and it often yields sub-optimal solutions [4], [5]. This may not be suitable for real-time accurate forecasting purpose. Recent attempt to use BP network for real-time flood prediction has lead to relatively poor performance particularly for peak flows [6].

This paper investigates the effectiveness of recurrent neural networks (RNN) dynamic for real-time reservoir inflow forecasting. In addition, we evaluate the RNN against operational statistical and physical-based prediction methods. Our contribution is divided into three sections. First, the proposed method (RNN) and the selected operational models are presented. Secondly, experimental results are reported, and finally some conclusions are drawn.

Recurrent Neural Networks

The RNN used in this study is the Elman RNN [7] that has feedback connections from its hidden neurons back to its inputs (Fig. 1). This is a discrete time two layer network with five hidden nodes and one output neuron. As the network geometry is problem dependent, here the number of hidden nodes has been selected using the common trial and error method. The network is trained in the conventional supervised manner by optimizing a performance index (E) using a second order nonlinear optimization method known as the Levenberg-Marquardt Backpropagation (LMBP) [8]. The LMBP uses the approximate Hessian matrix (second derivatives of E) in the weight update procedure as follows

$$W_{k+1} = W_k - [H + \mu I]^{-1} J^T r \qquad (1)$$

where r is the residual error vector, μ is small scalar, $J = \nabla E$ is the Jacobian matrix, and $H = J^T J$ denotes the approximate Hessian matrix usually written as $\nabla^2 E \cong 2J^T J$. This method requires more computation per iteration than the BP algorithm. To

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reduce the network training time, the LMBP is used with an early stopped training criterion [9] given by

$$GR(t)=100\left[\frac{E_{val}(t)}{E_{low}(t)}-1\right] \tag{2}$$

where $GR(t)$ is the generalization loss at epoch t, $E_{val}(t)$ is the average validation error over the validation set, and $E_{low}(t)=minE_{val}(t')$ with $t'\leq t$ is the lowest error obtained in epochs up to t. Generalization loss is obviously a serious reason to stop training. This training approach highly reduces the RNN training time, hence allows the model to be retrained on-line to adapt to changing future events. The method also takes advantage of the internal recurrence to dynamically incorporate past experience in the training process.

To perform the multi-step ahead forecast, we use a recursive method. The network performs a single step ahead forecast recursively to attend the k-step-ahead forecast as follows

$$\begin{aligned}
&\hat{y}(t+1)=f_1(x(t),x(t-1),\cdots,x(t-n))\\
&\hat{y}(t+2)=f_2(\hat{y}(t+1),x(t),x(t-1),\cdots,x(t-n))\\
&\vdots\\
&\hat{y}(t+k)=f_k(\hat{y}(t+k-1),\hat{y}(t+k-2),\cdots,\hat{y}(t+1),\\
&\qquad x(t),x(t-1),\cdots,x(t-n))
\end{aligned} \tag{3}$$

where $x(t)$ is the observation at time t, $\hat{y}(t)$ is the forecast at time t, f is the function estimated by the network. Here the outputs of the network depend on an aggregate of the previous states and the current inputs. The recursive forecast method may be better than the direct multiple-period forecast which rely only on the past observations to directly predict future points.

Description of Selected Forecast Models

A conceptual model (PREVIS) maintained by the Energy Division of Aluminum Company of Canada (Alcan) for real-time reservoir operation is considered as a first benchmark. The PREVIS model is an extended version of the global conceptual model proposed by [10] for the Canadian watershed. The model structure incorporates interconnected conceptual storage systems that are found to have significant contribution to the generation of streamflow. In this study, the PREVIS model is calibrated using the same data as those of the RNN and the statistical models presented here after. In order to improve the predictions accuracy, a correction procedure is applied to the PREVIS model output as

$$\hat{y}_{corr}(t)=\hat{y}(t)+(y(t-1)-\hat{y}(t-1)) \tag{4}$$

where $\hat{y}_{corr}(t)$ and $\hat{y}(t)$ are corrected and predicted forecasts at time t respectively.

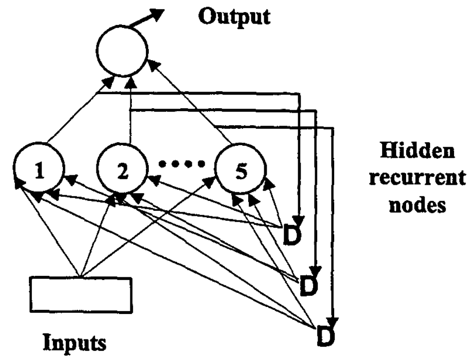

Fig. 1. Elman RNN used to forecast hydroelectric reservoir inflows. **D** represents a delay unit.

The second benchmark is an ARMAX (autoregressive moving average model with exogenous variables) model [11] which has been widely used for hydrologic forecasting. For the regression method, the outcome is related to the linear combination of the independent variables assuming a functional form. In our case, the forecasted natural inflow $\hat{y}(t)$ is related to the past outcomes $\hat{y}(t-i)$, inputs $x(t-j)$, and model error $e(t-j)$ assuming a linear autoregressive moving average with exogenous inputs model formulated as

$$\hat{y}(t)=-\sum_{i=1}^{n_a}a_i\hat{y}(t-i)+\sum_{j=1}^{n_b}b_jx(t-j)+\sum_{k=1}^{n_c}c_ke(t-k)+e(t) \tag{5}$$

where n_a, n_b, n_c, are the number of past outputs, inputs and error terms, respectively, a_i, b_j, c_k, are the model parameters to be estimated, and $e(t)$ is the model error. It is straightforward from (5) that the method uses a single function to iteratively predict future events. In this case, the regression function identified by [12] using the same hydrological time series is considered. This model is formulated as follows

$$\begin{aligned}
\hat{y}(t)=&a_1\hat{y}(t-1)+b_{11}x_1(t)+b_{21}x_2(t)+b_{31}x_3(t)+\\
&\sum_{j=0}^{4}b_{4,j+1}x_4(t-1)+\sum_{j=0}^{4}b_{5,j+1}x_5(t-j)+e(t)
\end{aligned} \tag{6}$$

where x_1, x_2, x_3 represent the maximum, minimum and mean temperature, x_4 and x_5 are precipitation (rainfall) and snowmelt respectively. It is can be seen from (6) that the model use 14 exogenous input variables to predict the outcome $\hat{y}(t)$. In order to perform daily adjustment of the estimated parameters, the Kalman filter (KF) is coupled with the ARMAX model and the final model is referred to as ARMAX-KF (autoregressive moving average model with exogenous variables and with Kalman filter).

Experiment and Results

Data for the experiment were taken from Chute-du-Diable watershed in northern Quebec (Canada). The original data consist 32 years (1964-1995) of daily natural inflows, estimated daily precipitation (rain and snow) and snowmelt, daily maximum, minimum and mean temperature. We used 29 years (1964-1992) of daily records for the models training and the last 3 years (1993-1995) for the prediction. Since we use the early stopped training approach, the training set is split into two subsets: the first one (1964-1980) is used for the network training, and the second one (1981-1992) for the cross-validation. In this experiment, accurate one week ahead forecast of the spring term water inflows is of particular interest.

To evaluate the models performance, three performance validation are used. The RMSE (root mean square error) is used as the common performance measure as it weights heavily larger forecasting errors. To estimate the efficiency of the fit, the R^2 efficiency [13] is used. It can be estimated from

$$R^2 = 1 - \frac{\sum_{p=1}^{n} (\hat{y}_p - y_p)^2}{\sum_{p=1}^{n} (\bar{y}_p - y_p)^2} \tag{7}$$

The optimum R^2 value is unity. As the accurate forecast of peak flows is highly important for hydropower reservoir operation, a peak flow criteria (PFC) is also considered. It can be specified as

$$PFC = \frac{\left(\sum_{p=1}^{n_p} \left(y_p - \hat{y}_p \right)^2 y_p^2 \right)^{1/4}}{\left(\sum_{p=1}^{n_p} y_p^2 \right)^{1/2}} \tag{8}$$

where n_p is the number of peak flow greater than one third of the mean peak flow observed. PFC provides accurate measure of the model performance for flood periods. A PFC equal to zero represents a perfect fit.

The models RMSE and R^2 statistics for the three year validation period are summarized in Table 1. In general, from Table 1 it is clear that the RNN provides the most accurate predictions for all the forecast horizons. The ARMAX-KF model outperforms the PREVIS model only for 1 to 2 day ahead forecast. Conversely, the PREVIS model is better than the ARMAX-KF for 3 to 7 day ahead forecast. The R^2 statistics for the ARMAX-KF model decrease rapidly with the increase of the forecast horizon. Therefore the ARMAX-KF is not adequate for more than two day ahead forecast. This is one of the main limitation of the Box and Jenkins [11] iterative forecast method. The trend of R^2 efficiency reveals that the PREVIS model behave like the RNN model, but it provides less accurate forecast than the latter.

Table 1. Models performance in terms of RMSE (m^3/s) and R^2 (in parenthesis) averaged over the test period (1993-1995). Results for ARMAX-KF are from [12].

Forecast horizon (day ahead)	Model		
	PREVIS	ARMAX-KF	RNN
1	97.02 (0.880)	64.14 (0.951)	35.83 (0.987)
2	106.45 (0.858)	99.92 (0.885)	31.95 (0.989)
3	112.63 (0.841)	129.58 (0.809)	34.05 (0.988)
4	118.31 (0.825)	152.05 (0.740)	34.44 (0.988)
5	124.56 (0.804)	170.13 (0.677)	31.18 (0.990)
6	130.95 (0.781)	185.14 (0.618)	33.43 (0.988)
7	136.39 (0.760)	198.45 (0.562)	29.58 (0.991)

Table 2. Model PFC performance averaged over the test period (1993-1995). Smallest PFC values indicate best forecast accuracy. Results for ARMAX-KF are from [12].

Forecast horizon (day ahead)	Model		
	PREVIS	ARMAX-KF	RNN
1	0.185	0.140	0.065
2	0.195	0.187	0.062
3	0.200	0.217	0.067
4	0.203	0.236	0.069
5	0.208	0.249	0.057
6	0.212	0.260	0.054
7	0.216	0.270	0.058

To examine the models performance during the spring flood period, the peak flow criteria (PFC) statistics are presented in Table 2. The PFC statistics clearly indicate that the RNN is the most accurate for the high flow forecasting and particularly for 5 to 7 day ahead forecast. As can be seen from Table 2, the PREVIS model outperforms the ARMAX-KF for 3 to 7 day ahead high flow forecast. The latter provides accurate high flow forecast only for the two first of the seven days. In general, using the RNN, the peak flow forecast accuracy can be improved in average by a factor 3 and 4 with comparison to the PREVIS and ARMAX-KF respectively.

Conclusion

The first goal of this paper has been to apply RNN to the problem of accurate short-term forecasting of hydropower reservoir inflows. From the generalization performance obtained, the proposed method appears to be an effective tool for multi-step ahead real-time hydrologic forecasting. The comparison of the RNN performance with those of the ARMAX-KF and the PREVIS shows that the RNN has significantly better prediction accuracy than these models. Overall the RNN is also the most accurate predictor for the spring flood period. Moreover, the low variability of the prediction performance with the increase in the forecast horizon, suggests that the method is robust and adequate for dynamic on-line water inflows forecasting.

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