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DEVELOPMENT OF A REAL-TIME RIVER FLOOD FORECASTING TRANSFER FUNCTION-NOISE MODEL WITH A KALMAN FILTER FOR SNOWMELT DRIVEN FLOODS

Jan Adamowski[1]
Kaz Adamowski[2]

[1] Massachusetts Institute of Technology, Cambridge, MA, USA
[2] University of Ottawa, Ottawa, Ontario, Canada

A real-time flood forecasting model for the Rideau River in Ottawa, Canada was developed for issuing flood warnings with sufficient lead-time. A Transfer Function-Noise (TFN) stochastic model coupled with recursive parameter estimation via a Kalman prediction algorithm was used to forecast the spring flood at the Ottawa gauging station using an upstream station (at Manotick) and tributary flows (at Jock River) as model inputs. Also, spring snowmelt runoff computed using mean daily temperature, snowfall and areally averaged snowdepth was explicitly represented in the model. The model was calibrated and tested on spring flood data from 2002 and 2004. Comparison of forecast results for a six hour lead-time showed that the new model is better suited to the Rideau River flow than the previously developed Self-Tuning Predictor (STP) model.

INTRODUCTION

Real-time hydrological forecasts are required for a variety of purposes within the framework of the overall operational control of water resources systems and include flood forecasts, reservoir operation, and water quality control.

Different types of real-time models whose properties can be broadly specified as linear or non-linear, stationary or non-stationary, deterministic or stochastic, single-input or multi-input have been used for the forecasting of floods. Real-time flood forecasting for a complex basin including lakes, snowmelt and precipitation spatial variabilities is a manifold challenge.

In this study, a novel flood forecasting model for the Rideau River in Ontario, Canada was developed. Flood forecasting for the Rideau River watershed in Ontario is one of the most important tasks that the Rideau Valley Conservation Authority (RVCA) faces. The RVCA issues forecasts at twelve different locations in the watershed including five sites within the city of Ottawa. The RVCA authority currently employs a method of flow forecasting using an empirical relationship between snowpack water equivalent and annual maximum discharge. It is a method based upon a correlation between average snowpack depth on the watershed at a particular site before the annual maximum discharges as measured at the flow gauge where the forecast should be made. By applying subjective judgement after inspection of the spatial distribution of snow course data, an indication of how the flood risk may vary from point to point in the watershed is provided. This method can be characterized as an intuitive/graphical method. However, as a result of repeated flooding in the watershed, the RVCA recognized the need to have a reliable real-time operational forecasting model which would rely less upon the forecaster's intuition and familiarity of the watershed.

As such, in 1989, the RVCA initiated a study for the development of a Rideau River flood forecasting model for issuing flood warning with sufficient lead time to allow appropriate emergency action (Bishop, 1989). The RVCA stipulated that the lead-time should be six hours. The result of this study was the development of a Self-Tuning Prediction (STP) algorithm developed for the RVCA by Bishop et al. (1989) which was based on Autoregressive Moving Average (ARMA) time series analysis.

The prediction equation is given by (Bishop, 1989)

$$Y(t + k/t) = -\alpha(q^{-1})\, y(t + k - 1 / t - 1) + \beta(q^{-1})\, u(t) + \gamma(q^{-1})\, e(t) \tag{1a}$$

where $y(t)$ are water level time series for time t = 0, 1, 2, 3,…, $e(t)$ is a Gaussian white noise sequence, k is the forecast lead time, $u(t)$ are the upstream discharge observations, and the operator polynomials are (Bishop, 1989)

$$\alpha(q\text{-}1) = \alpha_1 + \alpha_2 q^{-1} + \dots + \alpha_l q^{1-l} \tag{1b}$$

$$\beta(q\text{-}1) = \beta_1 + \beta_2 q^{-1} + \dots + \beta_m q^{1-m} \tag{1c}$$

$$\gamma(q\text{-}1) = \gamma_1 + \gamma_2 q^{-1} + \dots + \gamma_n q^{1-n} \tag{1d}$$

where l, m, and n are the orders of the operator polynomials.

Between 1989 and 1993 the RVCA tested both the intuitive/graphical and STP methods. Unfortunately, the STP forecasts were less accurate than the forecasts using the intuitive/graphical method. As a result, the RVCA ceased using the STP model and once again began to use the intuitive/graphical method.

After examning the STP model, it became evident that one of the major weaknesses was in the selection of significant flood contributing hydrological variables and the mathematical representation of the underlying physical processes. In particular, snowmelt was not taken into account. Spring floods in the Rideau River not only originate from the incremental flow from upstream and tributaries, but also from precipitation and spring snowmelt.

The purpose of this research was to develop a Transfer Function-Noise model (Salas et al., 1980), along with a Kalman Filter as a recursive algorithm for one step ahead (t+1/q) forecasting of the state vector (ie discharge), given measurements and values of the state up to time t. An important component of this model was the explicit inclusion of snowmelt. The proposed model was calibrated and tested using observed data and the results were compared with the existing STP model.

STUDY AREA AND DATA

The Rideau River watershed has an area of 3833 km^2 which can be classified into two distinct areas. Upstream of Smiths Falls is the lake region which has a hilly, uneven topography intersperced with a large number of lakes. Downstream of Smiths Falls is very flat, often swampy, and contains very few lakes.

The Rideau Canal system is the main feature of the Rideau River watershed. It is on the main channel of the Rideau River over much of its length and links Kingston on Lake Ontario and Ottawa on the Ottawa River. Many structures were constructed as part of this system to maintain navigational levels in the waterway.

The Rideau River has a number of tributaries which include: the Jock River, Steven Creek, Kemptville Creek and the Tay River. As identified by the RVCA and the developers of the STP model, there are nine stations in the watershed at which forecasts are needed. However, the Rideau River at Ottawa is the most important station at which flow forecasts are required, and in particular during the spring. It is for this reason that this site was chosen for this study.

Stream flows have been gauged at stations listed in Table 1 with the Water Survey Canada (WSC) code. Six-hourly spring flood data from 2002 and 2004 were used (since that is the lead time that has been stipulated by the RVCA) to calibrate and test the model presented in this paper, and to compare it with the existing STP model. Meteorological data such as temperature, rainfall and snowfall have also been collected at several sites in the watershed by the RVCA and the Atmosphric Environment Service (AES), and this data was used in the study. The meteorological station at Kemptville was selected as a reference station because it is centrally located in the watershed.

Table 1. Flow gauging stations for the Rideau River.

Gauge Location	WSC Station number	Drainage Area (sq.km)
Rideau R. at Ottawa	02LA004	3833
Rideau R. below Manotick	02LA012	3120
Jock R. near Richmond	02LA007	559
Kemptville Creek. near Kempville	02LA006	409
Tay R. at Perth	02LA016	786
Rideau R. at Becketts Landing	02LA010	2180

METHODOLOGY

Transfer function-noise model structure

It has been argued that deterministic, reductionist models are not appropriate for real-time forecasting because of the inherent uncertainty that characterizes river-catchment dynamics and the problems of model over-parametrization. Efficiently parametrized data-based mechanistic models, identified and estimated using statistical methods, have been shown to be very useful and are in an ideal form for incorporation in a real-time, adaptive forecasting system based on recursive state-space estimation (Young, 2002).

Several hydrological forecasting models have been proposed based on ARMA time series analysis and transfer function-noise analysis. Carson et al. (1970) used ARIMA models for the real-time forecasting of two headwater basins in Ontario. Wood and Szollosi-Nagy (1978) incorporated an ARMA model within a Kalman filter formulation allowing upstream flows and tributaries as inputs. Transfer Function-Noise (TFN) models with a linear relationship between input (rainfall) and output (runoff) were developed for three basins in Italy by Alsemo and Ubertini (1979). The Queen's University Forecasting Method (QUFM), developed by Watt and Nozdryn-Plotnicki (1981), uses an ARMA model and incorporates a loss submodel and a transfer function submodel. More recently, Ribiero et al. (1998) developed an ARMAX model coupled with a Kalman filter for real-time forecating of daily inflows in Quebec.

In the present study, a Transfer Function-Noise model with a Kalman recursive algorithm was developed with the following inputs: upstream flows, tributary flows, snowmelt and precipitation. The proposed Transfer Function-Noise model incorporates the relationship between winter snowfall and spring snowmelt runoff. It can be written in the following form

$$q(k+1)=\sum_{i=1}^{p}\phi_i q(k-i+1)+\sum_{j=1}^{r}\theta_j u_1(k-j+1)+\sum_{n=1}^{m}\alpha_n u_2(k-\delta-n)+u_3(k)+\eta(k)Y(k) \quad (2a)$$

$$Y(k)=q(k)+w(k) \quad (2b)$$

where $q(k)$ is the flow at the forecast station; $u_1(k)$ represents flow upstream of the forecast station or tributary; $Y(k)$ is flow at the forecast station with measurement error; $u_2(k)$ is the rainfall; $u_3(k)$ is the computed snowmelt runoff using the model structure developed in this paper; ϕ_i , θ_j , and α_n are model parameters; $\eta(k)$ is input noise; δ is the lag parameter between runoff and rainfall; $w(k)$ is the output or measurement noise assumed to be $N(w, R)$; and k is the time step (assumed to be 6 hours). The input noise is to account for the overall model inacurracy; it is assumed to be a moving average (MA) process and can be written as

$$\eta(k)=\varepsilon(k)+\sum_{f=1}^{z}\gamma_f \varepsilon(k-f) \quad (3)$$

where γ_f are the moving average model parameters and $\varepsilon(k)$ is $N(\bar{\varepsilon},Q)$ distributed.

Precipitation in the above TFN model is treated as an auxilliary input. While $u_2(k)$ represents rainfall, $u_3(k)$ models the seasonal snowmelt runoff and is initialized during snowmelt seasons. The runoff from rainfall is lagged in order to take into account the delay in the output peak flow hydrograph after a rainfall event. The delay time in the transport of the flow from upstream to downstream is determined from cross-correlation analysis of the flow records.

Snowmelt model

In terms of snowmelt models, the degree-day method is often used since it is one of the simplest among the large number of snowmelt models. However, it is a lumped model which does not include the areal variability in snowpack depth and many other factors that influence the quantity of snowmelt runoff. It is widely used because it is easy to implement and requires very few parameters to be estimated.

In this research, a more realistic snowmelt runoff model was introduced. It has two submodels: one for estimating snowmelt from snowpack depth, snowfall and temperature data, and another which transforms the melted snow into runoff. The snowmelt model is formulated to satisfy the following assumptions: (1) snowmelt occurs when the mean temperature is greater than a threshold air temperature T^o, assumed to be 0°C in the presence of sufficient snowpack depth; and (2) the snowmelt increases linearly with temperature. The snowmelt model equation which uses temperature and a direct relationship between the amount of total snowpack depth and the melting snow is given by Rodriguez (1994)

$$\mu(k) = (\alpha\kappa' + \beta)(T - T^o)\frac{D(k)}{\overline{D}_k} \tag{4a}$$

where

$$\overline{D}_k = \overline{D}_{k-1} + \frac{1}{k}(\overline{D}_{k-1} - a_4 SF_k) \tag{4b}$$

where $\mu(k)$ is the snowmelt runoff of day k (mm/day); $\alpha\kappa' + \beta$ is the degree-day factor (mm/°C) which increases with κ', the number of time steps from the start of the snowmelt period when $T > T^o$ (mm/°C); T is the air temperature index in °C; and T^o is the threshold air temperature below which no snowmelt occurs and which is assumed to have a parameter value of 1°C. $D(k)/\overline{D}_k$ is the lumped standardized water equivalent of snowpack at day k (mm); $D(k)$ is the snowpack depth during time period k (mm), D_k is the mean snowpack depth (mm); a_4 is a parameter that represents the proportion of daily snowfall quantity to be accumulated on the ground surface to form the snowpack; and SF_k is the snowfall depth over the time period k.

The exponential decaying function is used to express the contribution of snowmelt runoff computed using (4) to the river flow. The assumption is that when the temperature remains above 1 ºC for several successive days, the total snowmelt runoff during the time step k is the sum of snowmelts of current and previous time steps and is presented by the following formula

$$u_3(k) = a_1\mu(k) + a_1 e^{(-\frac{1}{k_s})}\mu(k-1) + \ldots + a_1 u(k) + a_1 e^{(-\frac{i}{k_s})}\mu(k-i) \tag{5a}$$

The time constant k_s for the exponentially decaying snowmelt runoff (5a) is

$$k_s = -\frac{1}{Ln(a_3^i)} \tag{5b}$$

where a_3^i is a time constant parameter. Equation (5a) can be reduced to a recursive equation of the form

$$u_3(k) = a_3 u_3(k-1) + ... + a_1 \mu(k) \tag{6}$$

where a_1 is the parameter specifying the proportion of the snowmelt $u(k)$ contributing to the river flow during time k, and k_s is the mean delay which is the time for (1-a_1) proportion of the snowmelt u(k) to be delayed before it contributes to the river flow.

In the case of non-consecutive warm temperature time steps, when $T(k-1) < 0$ and $T(k) > 0$, only the snowmelt $a_1\mu(k)$ in (6) generates the snowmelt runoff and contributes to the stream flow during k time step. The snowmelt as a result of warm temperatures during and prior to k-1, which is $a_3u_3(k-1)$, is assumed to refreeze due to the low temperature at k-1, and consequently it is assumed that it makes no contributions to the streamflow during k time step.

Real-time Kalman predictor

When designing a practical flood forecasting system, it is necessary to develop an appropriate mathematical model structure of the input-output process to allow reliable forecasts of a flood to be made in a real-time context. A real-time Kalman predictor is used as a recursive relationship which at the begining of each time step supplies the forecast of the future flow-rates on the basis of the current and past flow-rates as well as precipitation measurements and snowmelt.

The transfer function model in (2) and (3) can be employed in real-time forecasting first by estimating the model parameters using recursive parameter estimation techniques and by applying the Kalman predictor algorithm. The state-space representation of (2a) and (2b) have the following form (Iritz, 1992)

$$X(k+1) = \Phi X(k) + \Theta U(k-\delta) + \Gamma \varepsilon(k) \tag{7a}$$

$$Y(k) = \Psi X(k) + w(k) \tag{7b}$$

where Φ is a state parameter matrix; Θ is the input model parameter matrix; Γ is an input noise column vector; Ψ is the row vector; and the state vector *X(k)* is written as

$$X(k) = \left| q(k),...,q(k-p+1), u_1(k),...u_1(k-r+1), u_2(k-\delta-1),...,u_2(k-\delta-m), u_3(k), \eta(k) Y(k) \right|^T$$

where T is a matrix transpose.

The forecasting technique using the Kalman filter algorithms is contained with two steps: filtering and forecasting. The Kalman forecasting steps for (7) are written as

$$\hat{X}(k/k) = \hat{X}(k/k-1) + K(k)[Y(k) - \Psi \hat{X}(k/k-1) - w] \tag{8a}$$

$$\hat{X}(k+1/k) = \Phi \hat{X}(k/k) + \Theta U(k-\delta) + \Gamma \bar{\varepsilon}(k) \tag{8b}$$

where $\hat{X}(k+1/k)$ is the forecast of state $X(k+1)$ made at k time step, and $\hat{X}(k/k)$ is the filtered state, namely the a posteriori estimation of state *X(k)* on the basis of new available data *Y(k)*

Equation (8a) gives the correction of the forecast $\hat{X}(k/k-1)$ based on observed data, and is introduced into (8b) in order to achieve a better forecast of $X(k+1/k)$. $K(k)$ is referred to as the Kalman gain and is estimated using

$$K(k) = P(k/k-1)\Psi^T (\Psi P(k/k-1)\Psi^T + R)^{-1} \tag{9}$$

where $P(k/k-1)$ is the forecast error covariance matrix and R is the standard deviation of the measurement noise. It is estimated recursively using model parameter estimates, input and measurement noise covariances, and is given by

$$P(k/k) = \{I - P(k/k-1)\Psi^T[\Psi P(k/k-1)\Psi^T + R]^{-1}\Psi\}P(k/k-1) \quad (10a)$$

$$P(k+1/k) = P(k/k)\Phi^T + \Gamma Q \Gamma^T \quad (10b)$$

It must be noted that in real-time forecasting the type of forecast error correction method used can lead to considerable simplification of the model structure and this can result in relatively large errors in the flood forecasts. Two distinct forecast error correction approaches were used in this study.

Under the assumption that the parameter estimation error covariance matrix is linearly proportional to the prediction error (Kendall and Stuart, 1977), the STP model used forecast errors together with other variables as model inputs for updating model parameters and forecasting. The use of forecast errors as model inputs during parameter updating caused the propagation forecast error to be up to 25-30 time steps (Iritz, 1992).

Input noise covariance and Kalman gain play a relevant role in the Kalman predictor. Correction strongly depends upon the Kalman gain and the noise covariance. The correction during the filtering step prevents the forecast errors from propagating to the prediction of $X(k+1)$. Unlike the STP, the Kalman predictor allows separate treatment of the noise covariance; it is therefore useful to setup a scheme which, after each time step, supplies the re-estimation of the noise covariance, Q. Jazwinski (1970) proposed that such a re-estimation be made on the basis of the prediction performance in the previous time steps, which can be expressed as

$$Q(k) = [Y(k) - \Psi X(k/k-1) - w]^2 - \Psi\Phi P(k-1/k-1)\Phi^T\Psi^T - R \quad (11)$$

where the terms have previously been defined. For a meaningful interpretation of the noise covariance, in the case $Q(k)$ turns out to be negative, it is important to set $Q(k) = 0$.

Data treatment for calibration of snowmelt model

In order to produce six hour lead time flood forecasts using the model in (4) and (6), six-hourly temperature and snowpack water equivalent information are required. Because the available temperature data is on a daily time step, the following equations were used to calculate six-hourly temperature from minimum and maximum daily observed mean temperature data (Anderson, 1973)

$$T_{0-6} = 0.95T_{\min}(k) + 0.05T_{\max}(k-1) \quad (12a)$$

$$T_{6-12} = 0.4T_{\min}(k) + 0.6T_{\max}(k) \quad (12b)$$

$$T_{12-18} = 0.025T_{\min}(k) + 0.925T_{\max}(k) + 0.05T_{\min}(k+1) \quad (12c)$$

$$T_{18-24} = 0.33T_{\min}(k) + 0.67T_{\min}(k+1) \quad (12d)$$

where T is the mean six hourly air temperature, T_{min} is the minimum air temperature, T_{max} is the maximum air temperature and n is the current day.

Table 2 shows the depths and water contents of snowpacks that have been recorded every 15 days at five different locations on the Rideau watershed in 2002. The following formula gives the daily

Table 2. Snow data from five snowdepth measuring stations in 2002/03 (cm).

Day/ Month	Pierces corners	Wolford centre	Nolans corners	Ashton	Bells corners	Areal Mean depth	Water content
01/12	0	0	0	0	0	0	0
15/12	25.08	22.03	20.07	20.96	22.1	22.17	3.52
30/12	8.89	7.11	10	7.87	6.6	6.1	1.73
15/01	18.54	18.54	12.53	13.72	22.1	17.68	2.06
01/02	25.43	20.83	17.02	16.51	22.86	20.53	3.02
15/02	41.91	37.59	28.32	25.4	37.78	34.2	6.07
01/03	42.04	42.67	35.81	31.43	40.7	38.53	9.2
15/03	49.28	51.05	40.51	40.51	52.58	46.79	13.36
02/04	19.15	9.72	8.89	19.81	21.59	15.83	4.65
15/04	0	0	0	0	0	0	0

snowpack depth from the areally averaged 15 day interval snow water equivalent, daily snowfall and daily snowmelt

$$D(t) = D(t-1) + a_4 \sum_{i=1}^{15} SF(i) - \sum_{i=1}^{15} \mu(i) \tag{13}$$

where $D(t)$ and $SF(i)$ are the areally averaged 15 day interval observed snowpack and daily snowfall depths respectively, and $\mu(i)$ is the daily snowmelt. Formula (13) is then used to generate the six-hourly snowpack depth that is used to calculate the snowmelt water equivalent.

The daily snowmelt was computed using the degree-day method with a mean daily temperature and degree-day temperature index of 0.3 mm/ °C. The parameter a_4 was determined using a simple regression parameter estimation method and found to be 0.413. This parameter represents the proportion of daily snowfall quantity to be accumulated on the ground surface to form the snowpack.

It should be pointed out that the snowpack data obtained from snow course observations is not a very reliable indication of actual snowmelt potential. A better approach would be to use remotely sensed data instead of just standard, ten sample, snow course data. However, the use of remotely sensed data was not investigated in this study.

NUMERICAL ANALYSIS

An essential prerequisite in the application of the Kalman filter are model parameters and noise covariances. The time varying parameter set identifies the system model for the Kalman filter application. Cross-correlation analysis was performed to estimate delay time(s) between input and output flow series. Autoregressive orders for the input and output data were selected by applying the model for different orders of parameters. The best forecast model for the data being analyzed was selected based on minimum mean forecast error and standard deviation criteria.

The second step consisted of estimating the values of the parameters α, β and γ for the STP model and Φ_i, Θ_j and α_n for the TFN model, using the CLS (Constrained Linear Systems) method (Natale and Todini, 1976). The estimation was performed recursively at every time step t. The parameters for the forecast on June 2, 2004 at 0600, the last day of the data series are: $\alpha_1 = 0.90$, $\beta_1 = 0.18$, $\beta_2 = -0.21$, $\gamma_1 = 1.00$, $\Phi_1 = 0.90$, $\Theta_1 = -0.18$, and $\alpha_1 = 0.17$.

The performance of the developed model and the STP model was verified by calculating the forecast error, x_e, given by

$$x_e = x_t - x_o \tag{14}$$

where x_t and x_o are forecasted and observed flows, respectively. The standard deviation of the forecast error was also calculated, and is given by

$$\delta = \sqrt{\frac{\sum_{i=1}^{n}(x_{ei} - \bar{x}_e)^2}{n-1}} \tag{15}$$

where n is the number of observations, and x_e is the mean of the sample. The best model should have the smallest x_e and δ.

RESULTS AND DISCUSSION

The main objective of real-time flood forecasting is to predict the peak flow and the time of occurrence of this peak with sufficient accuracy. The peak observed spring flood of the Rideau River in 2002 and in 2004 and the corresponding forecasts obtained from the two models are displayed in Table 3. Forecast errors, standard deviation, mean error and mean percent error statistics are also included for the performances of the two models.

Table 3 shows that for the forecast of the peak spring flow of 2002, the forecast error of the TFN-Kalman with snowmelt model was 0.7 compared to 10.3 for the STP model. For the 2004 flood, the forecast error of the TFN-Kalman with snowmelt model was -5.8 compared to -10.7 for the STP model. One can also see from Table 3 that the TFN-Kalman with snowmelt model forecasts the flood peak in 2002 with a mean error of 0.2 versus 0.6 for the STP model, and 0.68 versus 0.93 for 2004, respectively. Due to the re-estimation of the noise covariance using (10), the propagation of forecast errors is greatly minimized. It was found that the STP model has a tendency to under-forecast the peak flow while the TFN-Kalman with snowmelt model has a tendency to over-forecast the peak flow.

Table 3. Comparison of forecasts for the peak observed flows in the spring of 2002 and 2004 (6 hour lead times).

Observed peak flow in 2002 = 282.3 m^3/s

2002	Forecast Peak Flow (m3/s)	Forecast Error	Forecast Error St Dev	Mean % Error	Mean Error
TFN-Kalman	283.0	0.7	8.1	2.3	0.2
STP	272.0	10.3	8.5	3.2	0.6

Observed peak flow in 2004 = 337.4 m^3/s

2004	Forecast Peak Flow (m3/s)	Forecast Error	Forecast Error St Dev	Mean % Error	Mean Error
TFN-Kalman	331.4	-5.8	7.1	3.46	0.68
STP	326.5	-10.7	8.3	3.70	0.93

CONCLUSION

A real-time flood forecasting model for the Rideau River was developed using a Transfer-Function Noise model with a Kalman Filter recursive algorithm along with a snowmelt model. A comparison of the results from the developed model and the existing STP model show that the TFN-Kalman with snowmelt model provides more accurate flow forecasts than the STP model. The model and its parameters and diagnostic checks ensure that the model operates optimally, and that its forecasts and parameters are updated in real time. It can be concluded that the model developed in this study offers an attractive alternative to currently used procedures in the Rideau River.

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ADDRESS FOR CORRESPONDENCE
Jan Adamowski
Massachusetts Institute of Technology, E40-476
77 Massachusetts Ave
Cambridge, MA, USA 02139-4307

Email: adamowsk@mit.edu