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THE EXISTENCE OF USEFUL VARYING PARAMETER SPACE FOR RIVER FLOW FORECASTING

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Abstract: Like any time series generated by complex systems, river flows can be represented by a time-varying parameter (TVP) model. TVP modeling frameworks often assume that the system evolution exhibits superstatistical random walks. Also, the TVPs should hone a predefined model ability to capture system's recurrence. In this work, we develop a computationally efficient method that extracts useful cyclic-type TVPs which are strongly coupled over extended, but more continuous and less aggregated, time horizons. A multi-level modeling framework is suggested to facilitate the creation and direct use of updated parameters. The modeling framework produce stable results of parameter variations at different time strings. The proposed framework can incorporate exogenous descriptors at different levels without loss of generality, and can be used in forecasting applications.

1 INTRODUCTION

It is undisputed that early flood warning efforts are becoming vital for many communities worldwide; such systems require reliable forecasts over extended horizons where weather information may not be available and also different from those usually referred to as long-term forecasts (Shiri; Kisi 2010). Long-term river flow forecasting studies have been dominated by statistical and deterministic based techniques (Atiya et al. 1999; Lucatero et al. 2018; Yaseen et al. 2018). Such techniques can successfully produce useful inferences in absence of information about the variables that drive river flows (Duan et al. 1992; Dye; Croke 2003).

The gap in the frequency, temporal resolution and aggregation size between short-term and long-term forecasts is ignored and implicitly justified, given the earlier limitation. Also, similar to any time series generated by complex dynamical systems, river flow has a time-changing pattern and, hence, can be represented by a model whose parameters change in time. This class of modelling approaches is usually referred to as time-varying parameter (TVP) modeling and originates from fields outside of water resource management and hydrology (Verdult; Verhaegen 2005; Viberg 1995). TVP modeling frameworks often exhibit stochastic properties, and relevant assumptions are utilized when building a model based on this view. However, the former become a subset of modeling frameworks when considering a broader class referred to as probability error methods. These statistical techniques have been developed in the literature and discussed in control system frameworks (Verdult; Verhaegen 2005; Viberg 1995).

In this work, we develop a computationally efficient method that extracts useful cyclic-type TVPs that are predictable. A modeling framework is presented, where a state defining procedure and state-updating-output-forecasting model are suggested. Linear regression is used to facilitate the creation and direct use of updated parameter states to produce far more reliable forecasts on the considered prediction horizons. Since there is no official test to TVP requirements, we also develop a simple testing strategy that utilizes an integrated multi-temporal grouping system-states and determines the requirement for the proposed model. The model does not require stochastic assumptions and can be formulated using a linear programing procedure. We apply the proposed model to forecast flows of the Clearwater River at different temporal resolutions and time horizons.

2 EXPERIMENTAL SETUP AND RESULTS

2.1 Data

The historical data of the Clearwater River, Alberta, Canada is considered. The drainage area served by the Clearwater River is measured to be 30,800 km² (RAMP 2012). Broach Lake in Saskatchewan, Canada, is the headwaters of the river at an elevation of 460 m. Also, it is estimated that only 20% of the total of a local basin, Athabasca basin, covers the drainage area of the river. The streamflow data (Q) is provided by Water Survey of Canada. Precipitation, snowmelt, relative humidity, minimum air temperature and maximum air temperature are obtained. It is observed that high flows often take place in spring, due to melting snow and seasonal rainfalls. In contrast, low flows take place in winter as precipitation takes the form of snow. Another observation is that extreme rainfall produced floods in summer. In hydrological events, the climatological variables may affect the streamflow with time delay. To illustrate this in the present case study, the correlation coefficients between each of the available variables and the streamflow at different lags were calculated as well as the streamflow autocorrelation. In this work, we are interested in forecasting the one step ahead of three different stream flows.

2.2 Method and Results

A free TVP model was first utilized to investigate the case study. The model takes the form:

[1] $Q(t) = \beta_o(t) + \sum_{i=1}^{k}\left(\beta_{t-i}(t) \times Q(t-i)\right) + e_t(t)$

where $Q(t)$ is the river flow at time t, $\beta_o(t)$ is the incidental model's intercept, $\beta_{t-i}(t)$ is the ith TVP of the search model, and $e_t(t)$ is the model's conditional error.

This model was used to derive optimal TVPs with a pattern search objective. The number of TVP variations was minimized over the considered time series. Also, the time series of the daily river flows were only used here. In this attempt, we investigate whether free-recurring TVP patterns arise from the optimization problem. Figure (1) shows the solution of the dynamical optimization problem over the case study and for a four-factor TVP model. It can clearly be noticed that the optimal TVPs do possess a recurring pattern on a long term bases; however, the obtained TVP solutions are hard to predict since there is no useful explanatories which can be extracted to predict future TVPs.

While the latter was a genuine TVP modeling framework, it is not the only valid approach to modeling dynamical systems with the varying parameter assumption. Hence, we develop a two-stage TVP modeling framework which attempts to capture predictable patterns of the obtained TVPs in the training stage. In summary, the high-level model is to derive the TVPs, and the low-level model is to get the flow forecasts. The proposed model takes the form:

[2] $Q(t) = \sum_{i=1}^{\tau} \beta_{t-i}(t) \times Q(t-i) + u$

[3] $\beta_{t-i}(t) = \sum_{j=0}^{p} \alpha_j \times Z_j(t) + \sum_{i=1}^{\tau}\sum_{k=1}^{\theta} \gamma_k^i \times \beta_{t-i}(t-k) + \epsilon$

[4] $0 \leq \beta_{t-i}(t) \leq 1$

where α_j and γ_k^i are the low-level model parameters of the j^{th} exogenous variable Z_j and the k^{th} high-level TVP of the i^{th} lag, respectively. In addition, u and ϵ are the high-and low-level residuals, respectively.

As shown in the formulation above, the proposed TVP model has the flexibility of utilizing exogenous variables which helps in deriving the useful TVP space. Moreover, k factors can be used to combine previous flow observations in order to forecast the upcoming flow rate. The γ_k^i parameters comprise the link between the proposed TVP models and the TVPs are constrained to fall in the range [0 1] for practical and technical reasons commonly known in the optimization practice. To demonstrate the effectiveness of the model, two different time horizons are considered. Figures 2 and 3 depict the obtained TVPs for 3-day ahead and 14-day ahead forecasting studies. It can be shown that the 3-day ahead TVPs do not demonstrate a cyclic behaviour, leading to a conclusion that TVPs for this temporal resolution may not be the best modeling approach for short-term forecasting. Even though the results of the modeling performance show significant forecasting performance of the proposed models, the cyclic behaviour is indicative of the generalization within the derived TVPs and should be an indication to the invalidity of the TVP assumption. On the other hand, the longer time horizon shows adequate cyclical patterns in the derived TVPs and is an indication of the model's generalization.

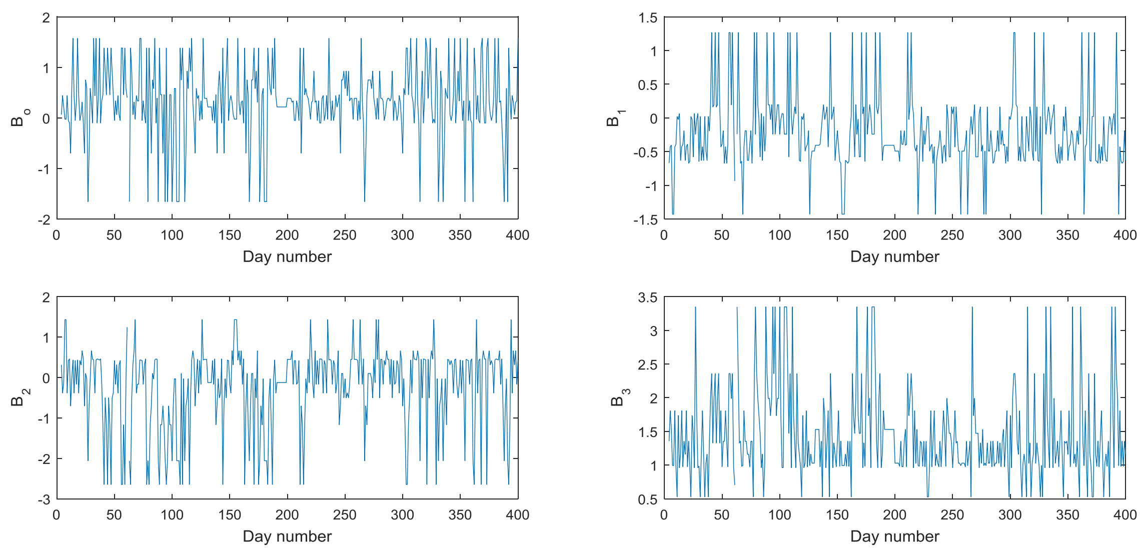

Figure 1: Evolution of a free four-factor model's TVPs for day-ahead forecasting over part of the case study.

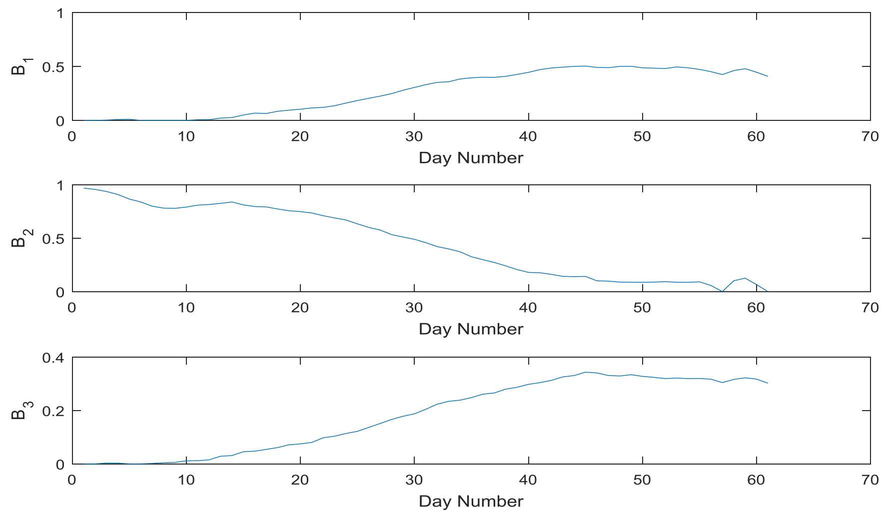

Figure 2: Evolution of the proposed three-factor model's TVPs for day-ahead forecasting over part of the case study.

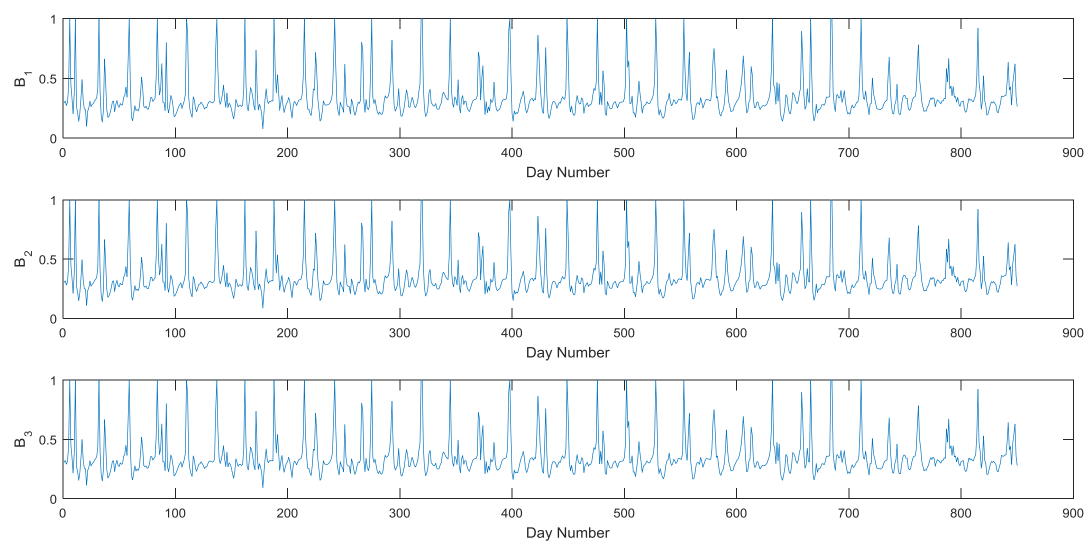

Figure 3: Evolution of the proposed three-factor model's TVPs for 14 day-ahead forecasting over part of the case study.

3 CONCLUSION

TVP approaches presents significant opportunity to design models sophisticated enough for a useful long-term forecasting effort. While TVP modelling is an open-ended research question, the present paper shows a promising approach which can be utilized to determine the applicability of dynamic modeling for a particular case study. In addition to the improved long-term forecasting performance, the results show the potential of developing a test which, in the case of streamflow forecasting, determines the temporal horizons for which TVP modelling is applicable.

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