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Recursively updating the error forecasting scheme of a complementary modelling framework for improved reservoir inflow forecasts

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SUMMARY

Reservoir inflow forecasting is an integral element of hydropower systems operation and is of paramount importance to hydropower producers. Effective forecasts directly impact power production scheduling, which in turn effects the revenues earned from power production. In this study, we implement a filter updating procedure (GU-COMP) that updates the gains on the error-forecasting component of a complementary forecasting framework (COMP) that also comprises a conceptual model with time invariant parameters. The GU-COMP procedure is applied for forecasting hourly flows of the Krinsvatn catchment (207 km^2; located in Norway) over a forecast lead-time of 24 h. The gain coefficients are considered as the only state variables and are updated daily using the error observed between measured and forecasted flows at the catchment outlet. The performance is rated based on evaluation of filter performance (i.e. convergence and consistency), and relative assessment of forecasting skills using the root mean square error (RMSE) and the percentage volume error (PVE) metrics. Bracketing close to 95% of the innovation sequences within two standard deviations from the mean, the filter is found to be well behaved. The RMSE and PVE metrics agree that GU-COMP outperforms COMP in reducing the forecast errors, and significantly altering distributional characteristics of the PVEs in the spring and summer seasons. It is also noted that the relative forecast accuracy enhancement diminishes for forecast lead-times beyond 20 time steps (hours).

1. Introduction

Reservoir inflow forecasting deals with estimating the amount of water that enters a given reservoir over a certain future time also known as forecast lead-time. It is a crucial element of reservoir operation planning and of paramount importance in maximizing the revenues of the hydropower producers from power productions. Over the past decades, mathematical models have seen wide range of applications in the field of hydrology, which includes use for describing the hydrologic behaviour of the headwater area of a reservoir. Despite numerous applications in real-life examples, hydrologic models are far from being perfect and improving reliability of the predictions has been important research topic.

Model updating has always been an indispensable tool of operational hydrologists ever since hydrologic forecasting began (Peck et al., 1980). Refsgaard (1997) defines model updating as a feedback process of assimilating measured data into the forecasting procedure before issuing a forecast. In the absence of formal mathematical techniques for evaluating hydrograph errors and implementing model updating, early forecasters employed the art of visualization to examine the disagreement between the forecasted flows and the observations, and used expert judgment to adjust some elements of the system subjectively in an effort to update the forecasting system (Peck et al., 1980). According to Houser et al. (2012), great strides towards successful application of objective model updating, often referred to as data assimilation (DA), techniques emerged as area of research in the science of hydrology in the last few decades ensuing the advances in measurement techniques that made possible arrival of more new hydrologic observations. DA procedures enable integration of recent measurements into the forecasting models when new observations become available in real-time and lead to more accurate hydrologic forecasts (cf. Georgakakos, 1995; Jønch-Clausen and Refsgaard, 1984; Kachroo, 1992). Here we invite interested readers to refer to Liu et al. (2012) for an extensive review of the progresses, potentials and challenges made in hydrologic DA, and to Moradkhani et al. (2012) for the latest theoretical advancement in hydrologic DA.

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Based on whether the variables modified during the feedback process correspond to the model inputs, model states, model parameters or model outputs, WMO (1992) defines four DA methods. Recent works have forwarded procedures for estimating state and parameters of a model jointly (e.g. Moradkhani et al., 2005a,b; Wang et al., 2009). The way the updating techniques are applied range from manual subjective trial and error approach (Ånund Killingtveit, Pers. Comm., June 2011) to formalized mathematical methods. These include recursive least square algorithms (e.g. Madsen and Skotner, 2005), Kalman filtering technique and its variant extensions (e.g. Ahsan and O'Connor, 1994; Canizaresab et al., 1998; Madsen et al., 2003; Pauwels et al., 2013; Refsgaard et al., 1983), variational data assimilation approach (e.g. Seo et al., 2003), and sequential Monte Carlo methods (e.g. Evensen, 1994; Moradkhani et al., 2005a). Depending on the manner the updating is conducted, these mathematical techniques belong to either variational or sequential DA methods (Drécourt, 2004). Variational DA methods operate in a batch-processing manner and have considerable computational cost as all available observations until the present time are used. Whereas sequential DA methods update the variables of interest in a sequential manner using only the most recent new observations. Sequential DA techniques suit themselves for undertaking hydrologic forecasting problems, which necessitate working with both past and future data, and are fast becoming the most popular approach to overcome the challenges hydrologist face in operational forecasting problems (e.g. Madsen and Skotner, 2005; Refsgaard, 1997).

The three features that determine quality of a hydrologic forecast (Moll, 1983) are the information about the system's past (right at the forecast issuing time), the amount of the future inputs into the system, and the description of the water movement in the system over the forecast horizon. DeChant and Moradkhani (2015) assert that enhancing performance of a forecasting system directly relates to reducing uncertainties in either the initial condition of the system, climate forcing or the forecasting model. Of these three sources of uncertainty, the extensive research the hydrologic community conducted in the last few decades primarily attempted to boost reliability of hydrologic forecasts by addressing uncertainty in modelling and model parameterization. This has led to formulation and implementation of various modelling concepts/approaches (Beven, 2012; Todini, 2007); calibration techniques (e.g. Boyle et al., 2000; Duan et al., 1992); uncertainty assessment methods (e.g. Ajami et al., 2007; Beven and Binley, 1992; Clark et al., 2008; Kavetski et al., 2003; Renard et al., 2010; Vrugt et al., 2008); and data assimilation (updating) techniques (e.g. Liu et al., 2012; Moradkhani and Sorooshian, 2008; Weerts and El Serafy, 2006). The other two sources of uncertainty (i.e. initial condition of the system and climate forcing) appear to be receiving attention recently. The initial state of a system summarizes the entire past and enables calculation of future responses of the system without reference to the historic inputs and outputs (Jayawardena, 2014). Among others, Wood and Lettenmaier (2008) Li et al. (2009), Shukla and Lettenmaier (2011), Yossef et al. (2013) characterize the relative contributions of the initial states and the climate forcing for improving skills of seasonal streamflow forecasting systems using ensemble-based approaches. They report that the initial state of the system plays important role on short-term streamflow forecasting even though the degree of influence varies across seasons, locations, and hydrometeorologic characteristics of the study areas. DeChant and Moradkhani (2011) demonstrate the role of DA in representing accurately the total seasonal flow uncertainty in snow dominated basins through initialization and characterization of the uncertainty in the initial states of the system.

However, implementation of the above methods in operational forecasting system is very limited (DeChant and Moradkhani, 2011). Challenge related to constructing the natural time lag between the variable to be updated and the flow observations (e.g. McMillan et al., 2013) is one factor limiting the use of DA techniques in operational hydrology. Other factors that hampered application of DA techniques operationally include computational burden and lack of mechanisms for objectively quantifying errors emanating from different uncertainty sources. The preferences of operational hydrologists to adhere to the current familiar models, which they can update manually is another issue worth mentioning. Liu et al. (2012) emphasize the need for DA research to undergo transition into delivering recognized operational tools. With this spirit, the current paper presents an effort being made by consortium of Norwegian hydropower companies and regulators to employ DA methods for improved short-term reservoir planning with the Elspot (a day-ahead) market of the Nordic exchange market as the centre of interest. The work presented in this paper attempts to mimic the normal operational practice in the Norwegian hydropower industry, which has long been framed to take the requirements for trading power in the day ahead market (Elspot) into consideration. The main features of the operational tradition emulated in this paper include issuing of forecasts before 12:00 CET and defining forecast window of 24 hourly time steps (12:00 CET to 11:00 CET next day).

In this study, we apply DA methods for improving skill of a forecasting system without assimilating data into the hydrologic model. Liu et al. (2012) describe that error-forecasting procedures improve forecasts by informing the forecasting system the future discrepancy between the model forecasts and future observations. The DA procedure we implement combines error forecasting with filtering and enhances the skills of a hydrologic forecasting model using the complementary modelling framework presented by Gragne et al. (2014). This complementary framework consists the semi-distributed conceptual model HBV (Bergström, 1995) and an autoregressive (AR) error model. The conceptual model represents the operational processes model whose parameters are unaltered throughout. The modelling framework identifies the order and structure of the AR model by making use of the bias, persistence and heteroscedasticity the residual series from the conceptual model exhibits.

The feedback process we set up on top of the complementary forecast system updates the error model using measured inflow data on a periodic basis without assimilating the data into the conceptual forecasting model. The extra information the most recent measurements provide serves to improve model forecast accuracy and constrain forecast uncertainty by updating the state of the error-forecasting model. In this paper, we introduce a multiplicative factor termed as "gain coefficient" as the only state of the error model. The gain coefficient (gain) is time variant and is updated continuously every 24 h. The main advantage of combining the updating procedure with the mentioned forecasting system is to extend the forecasting skill of the complementary framework way beyond the time horizon where the influence of the initial conditions of the hydrologic forecasting model are washed out (e.g. Madsen and Skotner, 2005). The most important feature of the present work is its attempt to improve reservoir inflow forecasts of an hourly model over a forecast lead-time of 24 h, on the basis of operational needs. It also suggests reducing the computational cost of DA by applying a DA technique on a simple error model for a deterministic forecasting system, which represents operational forecasting practice (e.g. Smith et al., 2012). The main objectives of the study are: (i) to improve accuracy of operational inflow forecasts at extended lead-times by recursively updating the error model; and (ii) to explore the potential of DA techniques, which combines a simple filtering procedure with a simple error-forecasting model in an operational setup without interfering with the operation of the conceptual model. In this study, we employ an adaptive Kalman filtering procedure (Almagbile et al.,