Journal of Hydrology 532 (2016) 52–64

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Review Paper

Reduction of the uncertainties in the water level-discharge relation of a 1D hydraulic model in the context of operational flood forecasting

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ARTICLE INFO

Article history:
Received 31 July 2015
Received in revised form 6 November 2015
Accepted 14 November 2015
Available online 1 December 2015
This manuscript was handled by Konstantine P. Georgakakos, Editor-in-Chief, with the assistance of Hamid Moradkhani, Associate Editor

Keywords:
Hydraulic modeling
Flood forecasting
Data assimilation
Uncertainty reduction

ABSTRACT

This paper presents a data-driven hydrodynamic simulator based on the 1-D hydraulic solver dedicated to flood forecasting with lead time of an hour up to 24 h. The goal of the study is to reduce uncertainties in the hydraulic model and thus provide more reliable simulations and forecasts in real time for operational use by the national hydrometeorological flood forecasting center in France. Previous studies have shown that sequential assimilation of water level or discharge data allows to adjust the inflows to the hydraulic network resulting in a significant improvement of the discharge while leaving the water level state imperfect. Two strategies are proposed here to improve the water level-discharge relation in the model. At first, a modeling strategy consists in improving the description of the river bed geometry using topographic and bathymetric measurements. Secondly, an inverse modeling strategy proposes to locally correct friction coefficients in the river bed and the flood plain through the assimilation of in situ water level measurements. This approach is based on an Extended Kalman filter algorithm that sequentially assimilates data to infer the upstream and lateral inflows at first and then the friction coefficients. It provides a time varying correction of the hydrological boundary conditions and hydraulic parameters.

The merits of both strategies are demonstrated on the Marne catchment in France for eight validation flood events and the January 2004 flood event is used as an illustrative example throughout the paper. The Nash–Sutcliffe criterion for water level is improved from 0.135 to 0.832 for a 12-h forecast lead time with the data assimilation strategy. These developments have been implemented at the SAMA SPC (local flood forecasting service in the Haute-Marne French department) and used for operational forecast since 2013. They were shown to provide an efficient tool for evaluating flood risk and to improve the flood early warning system. Complementary with the deterministic forecast of the hydraulic state, the estimation of an uncertainty range is given relying on off-line and on-line diagnosis. The possibilities to further extend the control vector while limiting the computational cost and equifinality problem are finally discussed.

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http://dx.doi.org/10.1016/j.jhydrol.2015.11.023
0022-1694/

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1. Introduction

Flooding causes important social, environmental and economic losses and is likely to be aggravated by climate change over the next decades. For example, flooding of the Var river in the South-East of France in 2010 resulted in a 700 million euros loss and 25 victims (MEDDE, 2011). Worldwide, national or international operational flood forecasting centers are in charge of providing water level predictions and flood risks at short- to medium-range lead time (from several hours to a few days) that are of great importance for civil protection. To this end, operational centers aim at providing an accurate forecast of the hydraulic variables (i.e., water level and discharge) along the monitored network. This forecast relies on the complementary use of numerical models and observations (Kirchner, 2006). For instance, the UK Environment Agency in collaboration with the Met Office has developed the National Flood Forecasting System (NFFS) in order to access to real-time forecasts from a large set of hydrologic modeling tools (Werner et al., 2009; Weerts et al., 2011). In the Philippines, the Metro Manila model is used operationally to issue 24-h lead time forecasts using precipitation and water level measurements that are collected and transmitted in real time (Madsen and Skotner, 2005). In France, since 2006, the national and hydrometeorological flood forecasting center (SCHAPI – Service Central d'Hydrométéorologie et d'Appui à la Prévision des Inondations), in collaboration with the 22 local flood forecasting services (SPC – Service de Prévision des Crues), produces a twice-daily vigilance map available for governmental authorities and general public (http://www.vigicrues.gouv.fr). Meteorological, hydrologic and geographic data (bathymetry, topography), are used as inputs to hydraulic models that are integrated in forecast mode to describe water level and discharge at a limited number of observing stations over 22,000 km of rivers in France. These hydraulic variables are then translated into a colored flood risk map available online. On a larger scale, the European Flood Awareness System (EFAS) as part of the Copernicus Emergency Management System provides probabilistic flood alert information more than 48 h in advance to national authorities. This alert system covers the main European rivers on a 5-km grid using a distributed hydrologic rainfall–runoff-routing model (LISFLOOD) as well as ensemble weather forecasts and real-time weather observations (de Roo et al., 2003; Van der Knijff et al., 2010).

The capacity for real-time anticipation of extreme flood events remains limited due to several sources of uncertainty in hydraulic models. On the one hand, forcing data that represent boundary conditions for hydraulic models usually result from the transformation of uncertain observed water levels into discharges with an uncertain rating curve (CEMAGREF, 1981; Audinet and André, 1995), or from discharges forecasted by uncertain hydrologic models. Another source of uncertainty is the description of the river channel and flood plain geometry. This requires on-site measurements of topographic and bathymetric profiles to provide a spatially-distributed geometry. On the other hand, the equations that are solved by models are based on simplification and parametrization of the physics. The parametrization schemes are calibrated to adjust the model behavior to observed water levels, typically, through the calibration of friction coefficients. The calibration of the river bed and flood plain friction coefficients is usually achieved once for all using a batch of observations such as water level from a limited number of flood events, thus providing time-invariant values for the model parameters. It is important to mention that errors in the model inputs and in the model equations are sometimes difficult to discriminate (Vrugt et al., 2005; Renard et al., 2010). These uncertainties usually translate into errors in the model representation of the water level-discharge (H–Q) relation that is not coherent with that from the reality. In practice, this inconsistency can be reduced when complementary data become available to improve the model, for instance LIDAR data for bathymetry (horizontal resolution of one point per square meter; 10–30 cm of vertical accuracy). When no additional data are available to improve the model geometry, the error between the simulated and the observed hydraulic states must be accounted for by adjusting the model parameters and/or the model state itself. Many studies have attempted to account for uncertainties at varying levels (Vrugt et al., 2008; Liu and Gupta, 2011), for instance by analyzing the uncertainty in hydrologic prediction based on the Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Freer, 2001; Aronica et al., 1998; Neal et al., 2007; Stedinger et al., 2008), Markov chain Monte Carlo (MCMC) (Jeremiah et al., 2011), Bayesian inference (Parrish et al., 2012) and Data Assimilation (DA) (Liu and Gupta, 2011; Moradkhani et al., 2005b; DeChant and Moradkhani, 2011a,b).

DA offers a convenient and cost-effective framework, compared to MCMC and Bayesian inference, to overcome some limits of the classical calibration process for model parameters: observations and simulation outputs are combined along with their respective errors to estimate an optimal set of model parameters and thereby reduce simulation uncertainties. Furthermore, as the DA algorithm is sequentially applied, the analysis allows for a temporal variation of model parameters errors. The classical approach in DA for meteorology and oceanography is to directly correct the model output variables (also called state estimation). In the hydrology and hydraulic literature, the estimation of uncertainty in model parameters has been extensively investigated in addition to the more traditional state estimation approach. DA is now being applied with increasing frequency to hydraulic problems with two main objectives (Liu et al., 2012): optimizing model parameters and improving stream low simulation and forecasting. Recent studies have shown the benefit hydrology and hydraulic can draw from the progress of DA approaches using either variational inverse problem (Valstar et al., 2004; Seo et al., 2003; Seo et al., 2009), particle filter (Dechant and Moradkhani, 2012), EKF (Thirel et al., 2010), EnKF for state updating (Weerts and El Serafy, 2006) or for dual state parameter estimation (Moradkhani et al., 2005b; Hendricks and Kinzelbach, 2008). Sequential state estimation for hydraulic applications was indeed found to have a limited impact on the forecast performance due to the limited persistence of the model initial condition. In contrast, the forecast lead time can be significantly improved via the correction of the hydrologic forcing (Hartnack et al., 2005; Andreadis et al., 2007; Ricci et al., 2011) or of the model parameters (Durand et al., 2008). Through the inclusion of parameters in the DA process, it is assumed that the forecast uncertainty can be efficiently reduced over a time window for which the errors statistics in the model parameters are stationary. State and parameter correction can be performed independently,