DYNAMIC CALIBRATION IN HYDROLOGIC AND HYDRAULIC MODELLING: EXPLORING THE POTENTIAL OF DATA ASSIMILATION FOR ESTIMATION OF MODELS' PARAMETERS

Miloš, Milašinović[1]
mmilasinovic@grf.bg.ac.rs

Andrijana, Todorović, Budo, Zindović
atodorovic@grf.bg.ac.rs, bzindovic@grf.bg.ac.rs

KEY WORDS

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ABSTRACT

Hydrological and hydraulic models used for forecasting and providing reliable inputs are essential for effective water management. Throughout their application, models might produce results of unsatisfying accuracy due to many uncertainty sources. Considerable uncertainty stems from model parameters values, which are usually obtained through calibration, i.e., iterative adjustment of the parameter values to achieve the best possible fit between simulated and observed variables. Model calibration yields time-invariant parameter estimates, which can lead to poor-quality simulation outputs that cannot serve as decision support. Specifically, parameter values can be expected to vary due to secondary- or seasonal processes that are not explicitly accounted for in the model, or due to anthropogenic activity (e.g., land-use change). Therefore, models used for operational forecasting should be run with up-to-date parameter values. This necessitates frequent model recalibration, which can be quite impractical due to high time- and computational requirements of the calibration procedure. Therefore, developing fast(er) calibration algorithms could be a viable alternative. This paper explores the potential of control theory-based, tailor-made, data assimilation algorithm intended for continuous update of the parameters of hydrological and hydraulic models. The algorithm enables the parameter values to be regularly updated at each computational time step based on the dynamically assessed goodness-of-fit (GOF) performance indicator. This approach enables one-pass calibration procedure. Using this algorithm instead of traditional, iterative calibration procedure where models' GOF is assessed at the end of the simulation, can improve efficiency and effectiveness of models' calibration. The proposed one-pass calibration approach will be tested on two synthetic test cases, one example of a hydrological model and one example of a 1D hydraulic model.

1. INTRODUCTION

Optimal daily use and control of water resources requires reliable decision support systems able to provide reliable forecasts of hydrologic data (stage and flow hydrographs) based on hydrologic and hydraulic models. Model-driven forecasting can be affected by numerous sources of uncertainty, such as unreliable initial and boundary conditions and/or poorly estimated model parameters [1], [2]. When model parameters are identified as the dominant source of uncertainty, additional attention should be addressed in model calibration. However, even the best calibrated models can produce results of unsatisfying accuracy due to secondary- and/or seasonal change of model's parameters or even anthropogenic impact (e.g., land use change). These parameters' dynamics often cannot be considered which can make the models unable to perform well on a daily basis. When operational hydrologic and hydraulic models are used for daily water management, calibration procedure must be repeated occasionally.

[1] Corresponding author

Additionally, using digital twins (DT) as a new (modelling) paradigm for operational water resources management [3]–[6] requires continually updated modes which amplifies the necessity for (near) real-time model recalibration. Traditional model calibration procedure is based on iterative adjustment of the parameters values to achieve the best possible fit between simulated and observed variables using empirical and/or some of the optimization algorithms. This algorithm provides time-invariant parameters, which means that model parameters are unchanged during the simulation, and every adjustment of the parameters requires a new simulation, which makes the traditional calibration procedure time-consuming, especially for operational models. On the other hand, numerous studies [7]–[15] showed the ability of data assimilation algorithms to update model parameters during the single simulation. However, these studies use ensemble-based data assimilation algorithms, where Monte-Carlo simulations have to be conducted, which, eventually, doesn't reduce the computational time significantly.

To deal with these problems, this research presents a novel data assimilation method for fast estimation of the model's parameters in a single simulation procedure. This method uses model predictive control where Proportional-Integrative-Derivative (PID) controllers are used to adjust model parameter(s) while satisfying the set of constraints. This method relies on previous studies [16]–[18] where control theory-based data assimilation (CTDA) is utilized to keep the model up-to-date considering only the model state (while model parameters were not considered). In this research, the existing CTDA method potential is investigated considering model parameters updating.

2. MATHERIALS AND METHODS

2.1 Methodology overview

This research proposes a model updating algorithm based on data assimilation. Here, observed, and simulated values representing the real-world system state and simulated (modelled) state are compared at each time step. This enables model parameter update accordingly (at each timestep) unlike the traditional approach where single goodness-of-fit (GOF) value is evaluated at the end of the simulation. The model and observation discrepancy is quantified using *error* variable which depends on model being updated (hydrologic or hydraulic). Based on estimated error value, PID controllers evaluate the correction of the model parameter. This procedure is repeated at each timestep (Figure 1).

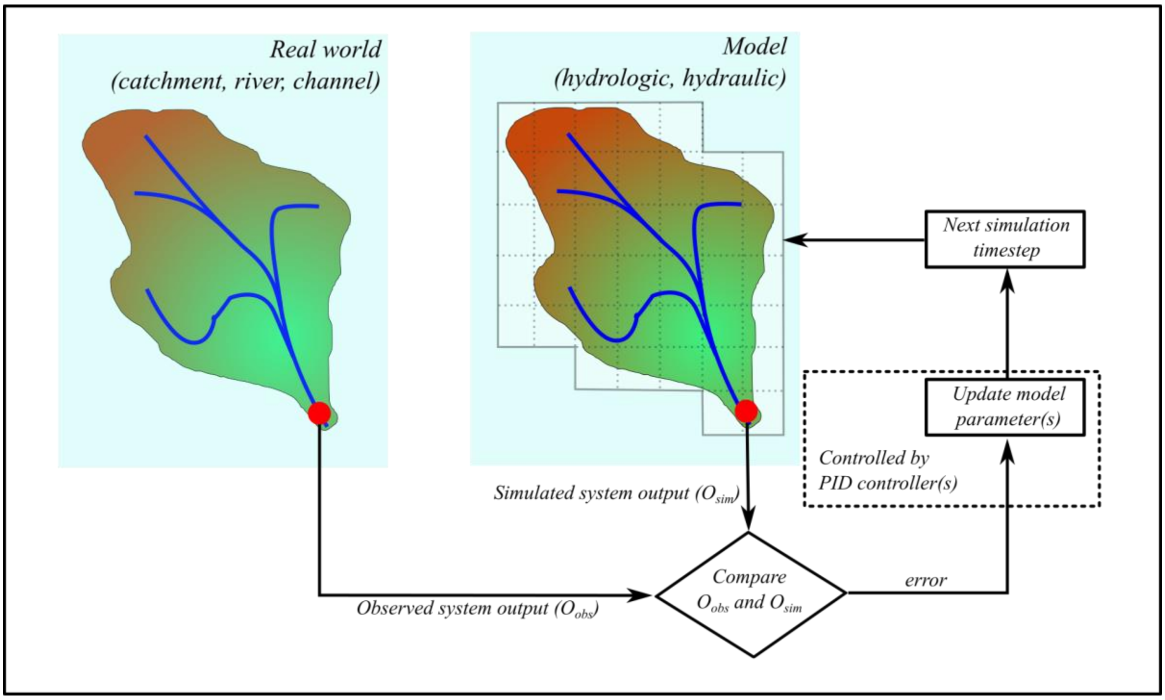

Figure 1: Fast data assimilation algorithm for updating model parameter(s).

2.2 Algorithm for continuous update of hydrologic model parameter(s)

In this study, rainfall-runoff process is approximated using simple nonlinear reservoir hydrologic model (Figure 2). Here, reservoir state is estimated using following balance equation:

$$\frac{dh}{dt} = P - i - \frac{Q}{A}, \tag{1}$$

where h represents water depth in the reservoir, P represents precipitation, i represents infiltration rate, Q represents surface runoff calculated using Manning's equation:

$$Q = \begin{cases} 0 & , h \leq h_s \\ \frac{1}{n} \cdot w \cdot (h - h_s)^{5/3} \cdot \sqrt{S} & , h > h_s \end{cases}, \tag{2}$$

In Manning's equation (eq. 2) w is approximated catchment width, h_s is maximum storage depth in the surface reservoir, n is Manning's roughness, S is average slope of the catchment and A is catchment area. In this case, Manning's roughness is considered as the main source of model uncertainty and parameter updating procedure is developed accordingly. Surface runoff (streamflow) is used as system output (Q_{sim} - simulated and Q_{obs} - observed). At each simulation time step process error $e(t)$ is calculated as a difference between Q_{sim} and Q_{out}:

$$e(t) = Q_{sim}(t) - Q_{obs}(t), \tag{3}$$

Process error value is used to calculate Manning's roughness correction Δn using PID controller's equation:

$$\Delta n = k_p \cdot \mathrm{e}(t) + k_i \cdot \int_0^t e(t)dt + k_d \cdot \frac{de(t)}{dt}, \tag{4}$$

where k_p, k_i and k_d are proportional, integrative, and derivative coefficients, respectively.

When Manning's roughness correction is estimated using equation (4), Manning's roughness value is updated for the next simulation time step:

$$n(t + \Delta t) = n(t) + \Delta n, \tag{5}$$

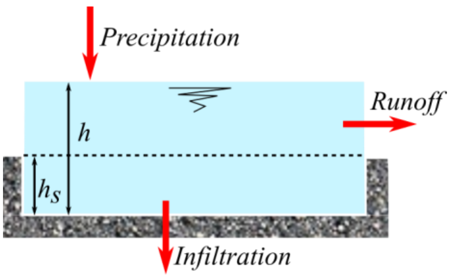

Figure 2: Non-linear reservoir hydrologic model.

2.3 Algorithm for continuous update of hydraulic model parameter(s)

Hydraulic model analyzed in this research is based on modified diffusion wave model ([17]), represented by the following form of the Saint-Venant's equations:

$$\frac{\partial Z}{\partial t} + \frac{1}{w} \cdot \frac{\partial Q}{\partial x} = 0, \tag{6}$$

$$\frac{\partial Q}{\partial t} + g \cdot A \cdot \frac{\partial Z}{\partial x} + g \cdot n^2 \cdot \frac{Q|Q|}{A \cdot R^{\frac{4}{3}}} = 0 \tag{7}$$

where Z is water surface elevation, w is the channel width, x spatial coordinate, t represents time, g is acceleration due to gravity, A cross section area, n is channel bed Manning's roughness, Q is flow and R represents hydraulic radius. The equations (6) and (7) are solved using explicit, staggered numerical scheme where Z and Q are calculated in alternating cross sections (Figure 3). Unlike hydrologic model, where flows are used as system output, in hydraulic mode water surface level (elevation) is used a system output because it represents less uncertain data and its lot easier and cheaper to measure than flow measurements. It is assumed that the main source of discrepancy between the model and observations is poor estimation of the Manning's roughness. To update Manning's roughness during the simulation, an updating procedure similar to hydrologic model parameter update algorithm has to be developed. However, since the open channel modelled by the proposed diffusion wave equations is a higher-order dynamic system than hydrologic model, single value of water surface level cannot be used to compare model and observations and correct model parameters. For example, when model is used for flood routing, water level obtained from the model where Manning's roughness is overestimated can be greater and lower than the observed water level depending on the part of the simulation (rising or recessional limb of the hydrograph). Therefore, different variable has to be used as system output. Here, a better representation of the system dynamics depending on the Manning's roughness is water surface level gradient. In that case, a simple rule can be applied to update the roughness parameter: when water level gradient obtained from the model is greater than the observed roughness parameter should be reduced and vice versa. The correction of the roughness parameter is controlled by PID controller. First step in this approach is estimate process error e(t):

$$e(t) = [Z_{obs}(t) - Z_{obs}(t - \Delta t)] - [Z_{sim}(t) - Z_{sim}(t - \Delta t)], \tag{8}$$

where Z_{obs} represents observed water surface level, Z_{sim} represents simulated water surface levels and Δt is simulation time step.

When the process error is evaluated, Manning's roughness parameter is updated using the equations (4) and (5).

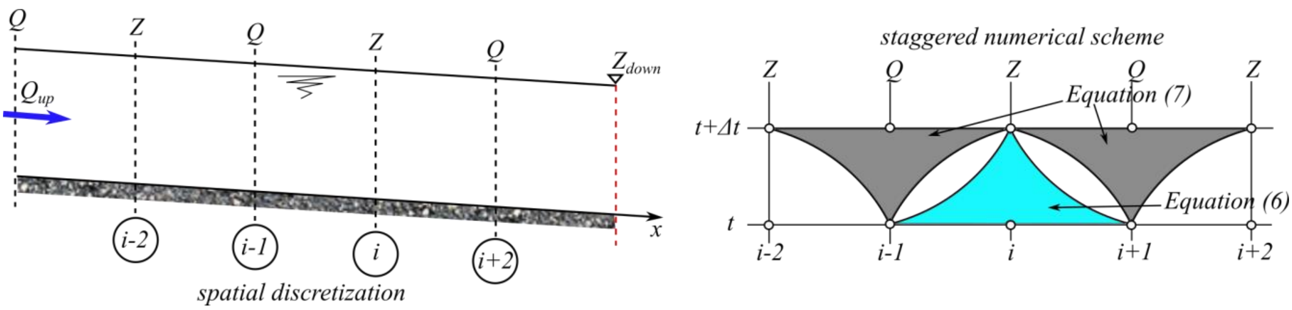

Figure 3: Hydraulic model discretization.

2.4 Test case 1 – Hydrologic model

To demonstrate the proposed parameter updating algorithm for hydrologic model, synthetic test case is used. Non-linear reservoir model is used to generate runoff from the synthetic catchment. The area of the catchment is 10 ha, width is 100 m, slope is 1‰, maximum storage h_s is set to 1 mm and infiltration rate is set to 0.01 mm/h. Initial value of water depth in the surface reservoir is set to zero. Simulation is run for the period of 20 h with 1 min timestep. True streamflows ("observed" data) are generated using the 0.025 $m^{-1/3}s$ value for Manning's roughness. After that, the model parameter is altered and assigned a value of 0.015 $m^{-1/3}s$ (Figure 4). This is used as the initial value and PID controllers are applied to update the parameter by minimizing the process error.

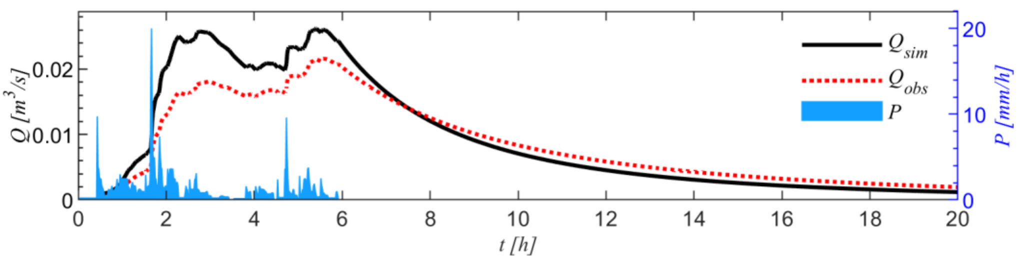

Figure 4: Synthetic test case scenario for hydrologic model assimilation.

2.5 Test case 2 – Hydraulic model

Test case scenario for hydraulic model is generated for a 1000 m long and 6 m wide rectangular channel, with the slope S = 0.2 %. The model is created using equations (6) and (7) discretized by six cross sections (1 to six going downstream) using the staggered numerical scheme (Figure 3) with Δx = 200 m spatial resolution and Δt = 20 s simulation time step. The true roughness parameter is set to 0.015 $m^{-1/3}s$ and this value is used to generate true model state ("observed" water levels). Upstream boundary condition is set to a constant flow value of 20 m^3/s and is also used as the initial condition for each cross section where flow is calculated. Value of 4 m is assigned as the initial value for each cross section where water surface level is calculated. The downstream boundary condition is represented by stage hydrograph (Z_{down} in Figure 5) and is used to generate transient regime. Only cross section 2 (closest cross section to the upstream boundary where water levels are calculated) is used as observation location. Simulation is run for the period of 6 h. After true data is generated, Manning's roughness value is changed to 0.025 $m^{-1/3}s$ and a new simulation is conducted where PID controllers are applied to update model parameter based on water levels assimilation.

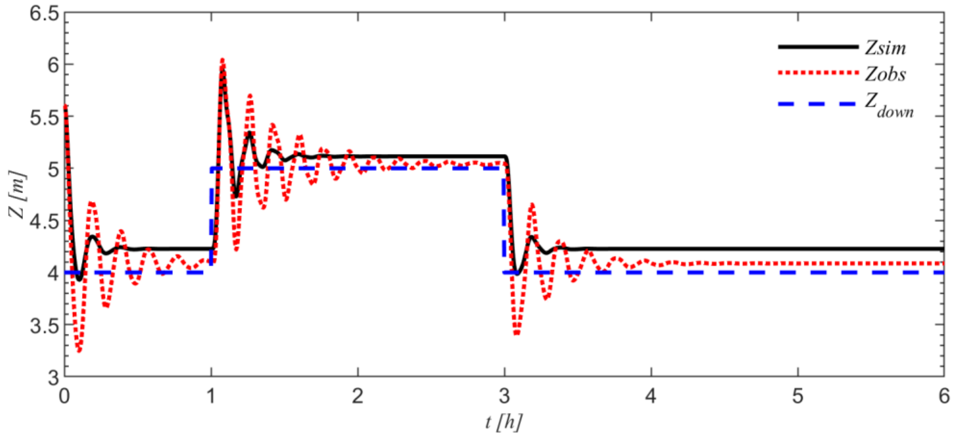

Figure 5: Synthetic test case scenario for hydraulic model assimilation.

3. RESULTS AND DISCUSSION

Hydrologic model streamflow data assimilation is conducted using PID controller with the following set of parameters: k_p = 1, k_i = 10^{-4} and k_d = 0. This PID controller configuration is able to assimilate streamflow data and reduce the process error close to zero. Accordingly, the value of the model parameter is updated to its true value at the very beginning of the simulation, approximately 85 min from the simulation start (Figure 6).

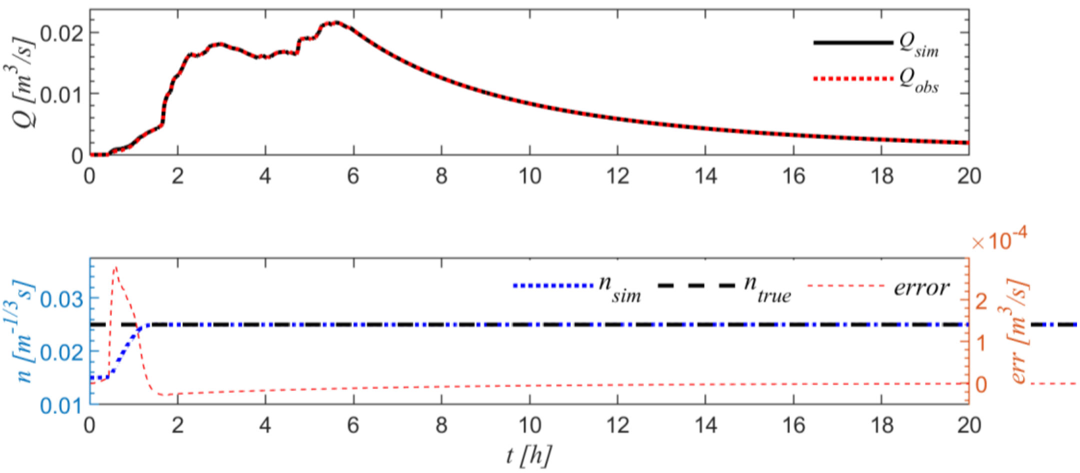

Figure 6: Synthetic test case scenario for hydraulic model assimilation.

Hydraulic model water surface level data assimilation is conducted using PID controller with the following set of parameters: k_p = 10^{-2}, k_i = 0 and k_d = 1. This PID controller configuration can assimilate water level data and reduce the process error close to zero. The value of the Manning's roughness is reduced to its true value relatively fast, approximately 3 h from the beginning of the simulation (Figure 7). Unlike the hydrologic model, where parameter model parameter is updated monotonously (always rises until it reaches true value), in hydraulic model PID controllers force roughness parameter to oscillate around the true value. The reason for this can be found in the higher-order system dynamic present in hydraulic model along with the effect of derivative coefficient in PID controller configuration. It has to be mentioned that different configurations of the PID controllers can give good results in updating model roughness parameter, but the tuning of the controllers should be carried out carefully because large values of the controller's parameters can make the model unstable.

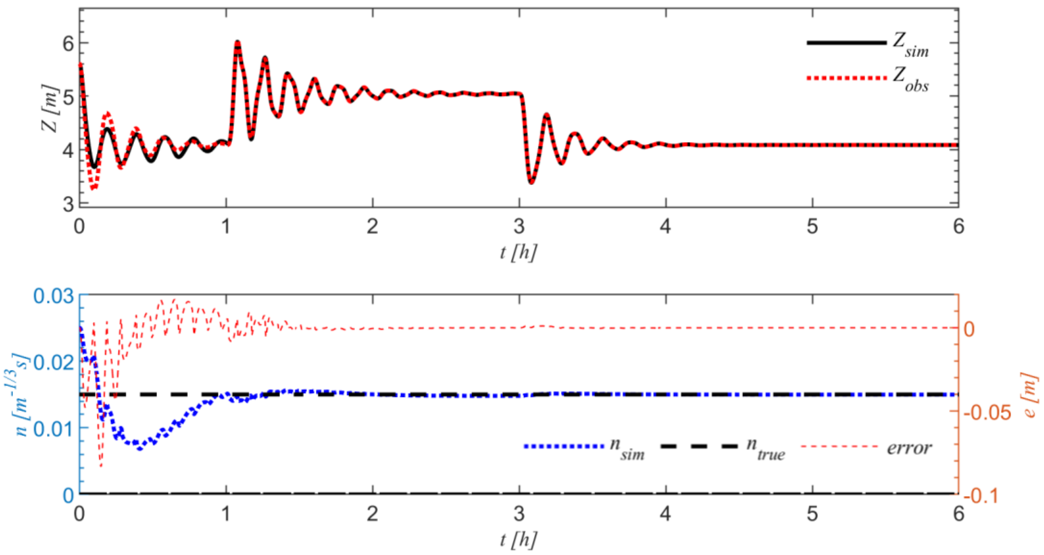

Figure 7: Synthetic test case scenario for hydraulic model assimilation.

4. CONCLUSIONS

This paper presents the potential of using fast data assimilation algorithm for continuous update of hydrologic and hydraulic model parameters. PID controller is applied as a data assimilation tool to reduce process error between simulated and observed system output. The analysis shows that PID controllers are able to update roughness parameter by assimilating streamflows (simulated and observed) in hydrologic model and water levels in hydraulic model. The proposed algorithm decreases computational time for model calibration thus enables the application in operational hydrologic and hydraulic models. However, for real-world applications, further investigations are necessary. The algorithm should be tested and eventually modified in cases when multiple model parameters have to be updated, when model uncertainty is also forced by unreliable input data (boundary conditions) along with poor initial estimation of the model parameters. Also, algorithm has to be analyzed in cases when there are multiple observation locations.

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