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► **To cite this version:**

N. Jean-Baptiste, C. Dorée, J. Sau, P.O. Malaterre. Data assimilation for the real-time update of a 1D hydrodynamic model, fault detection and correction – Application to the Rhône River. SimHydro 2010: Hydraulic modeling and uncertainty, Jun 2010, Sophia-Antipolis, France. 8 p. hal-00783030

HAL Id: hal-00783030

<https://hal.science/hal-00783030>

Submitted on 31 Jan 2013

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DATA ASSIMILATION FOR THE REAL-TIME UPDATE OF A 1D HYDRODYNAMIC MODEL, FAULT DETECTION AND CORRECTION – APPLICATION TO THE RHÔNE RIVER

Assimilation de données pour le recalage en temps réel d'un modèle hydrodynamique 1D, la détection d'anomalies et leur correction – Application au fleuve Rhône

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KEY WORDS

Estimation, Kalman Filter, Hydraulic, Control, Measurement uncertainties, Perturbation, State

ABSTRACT

Scarcity of water resource and increasing competition for its use promoted recently the development of advanced control algorithms and SCADA technologies for the automatic management of open-surface hydraulic systems. In order to control hydraulic devices on irrigation canals or rivers, detailed information on the hydraulic state of the system must be available. This is particularly true when the control algorithms are based on Linear Quadratic Gaussian or Predictive Control approaches using full state space models. Usually, the only known quantities are water levels, measured at limited locations. In this case, the design of an observer is a very useful tool for reconstructing unmeasured data, such as discharges or water levels at other locations, and unknown perturbations, such as inflows or outflows. Since the original work of Luenberger, state observers proved to be useful and are widely used in estimation and other engineering applications. In this line, the Kalman Filter, which provides a minimum variance recursive algorithm to optimally estimate the unknown states of a dynamic linear system with Gaussian uncertainties, has dominated the applications in signal processing and control areas. When the basic assumptions are not fulfilled, Extended Kalman Filtering (EKF) has been proposed to overcome its limitations. A portion of the Rhône River, between two hydropower plants managed by the Compagnie Nationale du Rhône, is modelled using the SIC hydrodynamic model. A Kalman Filter is then used, in a generic approach, to reconstruct unmeasured data, detect sensor faults and correct erroneous data. Real-time field data is used to validate the methodology.

RESUME

Assimilation de données pour le recalage en temps réel d'un modèle hydrodynamique 1D, la détection d'anomalies et leur correction – Application au fleuve Rhône.

La rareté de la ressource en eau et l'augmentation de la compétition pour ses usages a récemment favorisé le développement d'algorithmes de contrôle et des outils informatiques de supervision (SCADA) pour la gestion des aménagements hydrauliques à surface libre. Pour contrôler les ouvrages des canaux ou rivières, l'état hydraulique doit être fiable. Cela est particulièrement vrai lorsque le contrôle est basé sur l'approche Linéaire Quadratique Gaussienne (LQG) ou sur l'approche par commande prédictive. Généralement, les seules variables connues sont les niveaux d'eau mesurés en certains points. Dans ce cas, l'emploi d'un observateur d'état est utile pour estimer les données non mesurées telles que les débits et les cotes à d'autres endroits ainsi que pour estimer des perturbations inconnues.

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Depuis les travaux de Luenberger, les observateurs d'états ont prouvé leur utilité et sont fréquemment employés pour l'estimation et autres applications d'ingénierie. Dans ce même esprit, le filtre de Kalman basé sur des algorithmes de minimisation de la variance d'erreur reconstruit les états inconnus d'un système linéaire entaché d'incertitudes et de bruits blancs gaussiens. En présence de phénomènes non linéaires importants, le filtre de Kalman étendu (EKF) est mieux adapté. Une portion du Rhône entre deux aménagements hydroélectriques gérés par la CNR a été modélisée sous le logiciel SIC. Le filtre de Kalman a ensuite été utilisé pour reconstruire les données non mesurées, détecter les défauts des capteurs et corriger les données erronées. La méthodologie a été testée sur des données terrains.

1. INTRODUCTION

The Compagnie Nationale du Rhône (CNR) manages 18 hydropower schemes (19 hydropower plants and 19 dams). Given the absence of water storage at the different schemes, standard predictive control regulation algorithms were developed during a PhD thesis [1] and a major project: Rhône 2000. At present, 14 development schemes on the Rhone including the 12 on the lower Rhône (i.e. downstream of Lyon) are equipped with predictive control. This control improves the management of the development schemes on the Rhône, in particular in terms of conformity with operating instructions, as well as incorporating the constraints dictated by water levels and flow rates (and their gradients).

After five years of feedback from experience, it has been observed, in a general way, that a model embedded in the predictive control system provides a good basis for calculation as it relies on a large number of measurements transmitted from field stations. This ensures that regulation always matches realistic hydraulic conditions so that the control calculation strategy using the model and the simulated scenarios is reliable [2].

However, it has been observed that regulation by predictive control can be disturbed in the case of important errors occurring in the embedded model. Many uncertainties exist on the model parameters (change in the cross section geometry due to sedimentation, change in the roughness due to weed growth, etc.) and on the model inputs (inflows or outflows). In those cases, we can consider that the model no longer matches reality. Predictive control can also be disturbed by measurement uncertainties and measurement errors. That means when the measurements are corrupted by noise or when they are transmitted by faulty sensors. A methodology allowing to take into account all possible uncertainties, detecting the errors, correcting them and updating the embedded model is required. A previous method based on simple hydraulic calculation has been used for many years by CNR but needed to be improved.

A Kalman Filter, which is a data assimilation method, appears to be the most appropriate method for solving the problems generated by the uncertainties above cited. A study started in February 2008 and scheduled to end in February 2011 is being carried out in a view to test feasibility and performances related to the estimation/correction of water level and discharge all along the hydraulic system. This paper presents the hydraulic system considered and the underlining modelling and filter concepts. Then, the results obtained with some tests performed on a reach of the Rhône River are presented. Three scenarios have been selected to test the filter. The first one aims at detecting and correcting a sensor fault. The second one aims at reconstructing unknown inflows and the latest scenario presents a test on real field data with a sensor failure. For the three scenarios the considered inputs, measurements and model states are sullied with uncertainties.

2. THE HYDRAULIC SYSTEM CONSIDERED

A section of the natural Rhône is diverted via a bypass channel where a power plant and a lock (locks only between Lyon and the Mediterranean sea) are in place. A diversion dam is installed on the natural river channel to pass the floods (ref. Figure 1). Outside flood periods, this diversion dam diverts most of the flow to the power plant, thus creating a small reservoir upstream while allowing a constant minimum flow of compensation water along the old natural Rhône. The compensation water flow rate is determined by local authorities (from 5 to 150 m³/s, depending on the site).



Figure 1: Example concept of a development

A portion of the Rhône River, between two hydropower plants managed by the Compagnie Nationale du Rhône, is selected for this study (ref. Figure 2). The pilot development scheme is Baix le Logis Neuf. This system is controlled in real time using a predictive controller based on a full Saint-Venant embedded model.

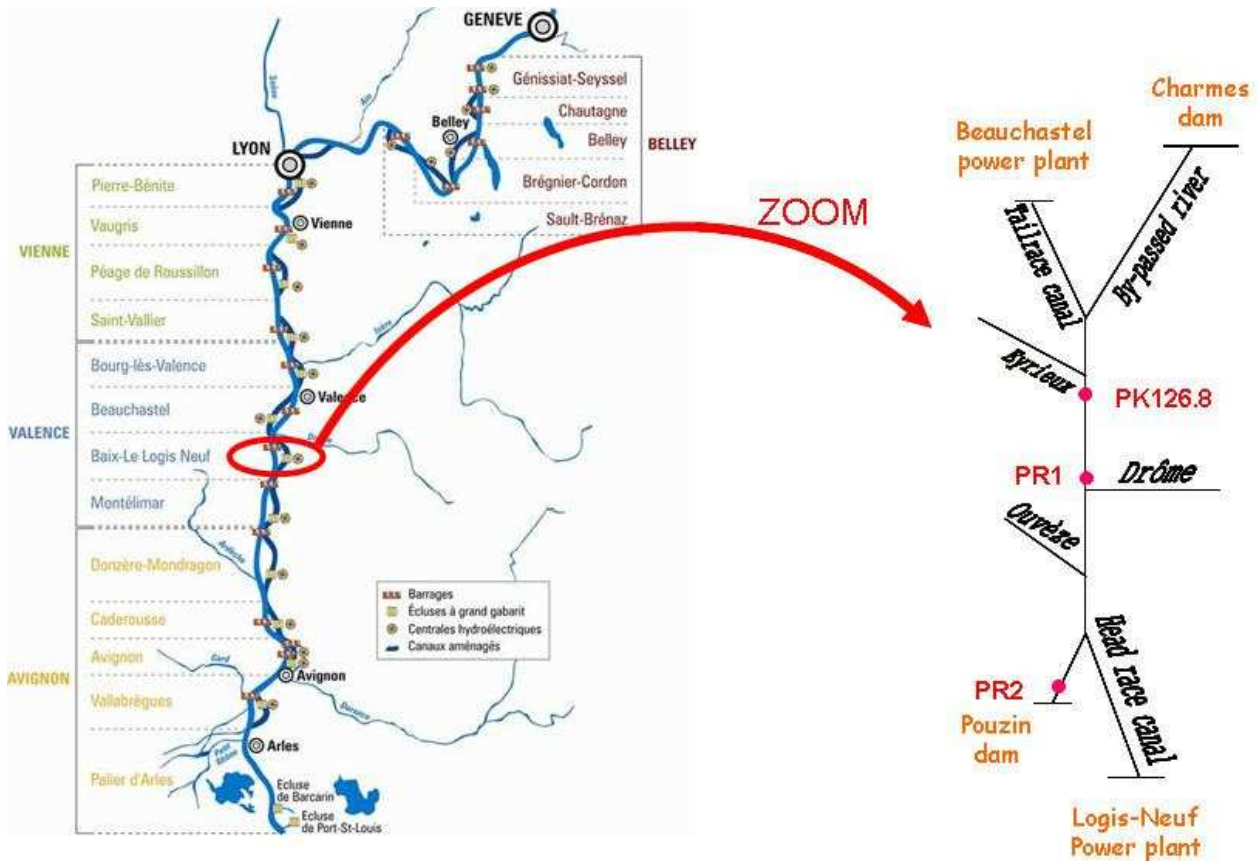


Figure 2: Developments schemes between Switzerland and the Mediterranean sea. Zoom on the pilot development scheme.

3. THE OPEN CHANNEL HYDRAULIC MODEL – THE NON LINEAR SYSTEM

3.1 The Barré de Saint Venant equations

In order to be well founded, a state estimation must be based on a proper modelling of the physical system. Cemagref is developing methodologies and software tools (the SIC hydrodynamic software) dedicated to consultant companies and canal or river managers allowing accurate hydrodynamic modelling [3]. This model is based on the 1D Saint-Venant equations. That means: the continuity equation (1) and the dynamical equation (2). The equations are completed by external and internal boundary conditions such as inflows and gate equations.

$$\frac{\partial S}{\partial t} + \frac{\partial Q}{\partial x} = 0 \quad (1)$$

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x} \left(\frac{Q^2}{S} \right) + gS \left(\frac{\partial Z}{\partial x} \right) = gS(I - J) \quad (2)$$

With:

- Q : Discharge (m³/s)
- Z : water elevation (m)
- S : Cross section (m²)
- I : Bed slope
- J : Friction slope
- t : Time (t)
- x : Longitudinal abscissa (m)
- g : gravity (9.81 m/s²)

In order to match the typical field operating conditions, the SIC software will perform successive time steps calculations, which will be called observation time steps. The numerical time step used in these successive calculations can be smaller, so as to obtain an accurate enough description of the open channel flow.

3.2 The discretization

The Barré de Saint Venant equations can not be solved analytically. We use the implicit Preissmann's discretization scheme [4]:

$$\begin{aligned} f(x, t) &= \frac{\theta}{2} (f_{i+1}^{n+1} + f_i^{n+1}) + \frac{(1-\theta)}{2} (f_{i+1}^n + f_i^n) \\ \frac{\partial f}{\partial x} &= \theta \frac{(f_{i+1}^{n+1} - f_i^{n+1})}{\Delta x} + (1-\theta) \frac{(f_{i+1}^n - f_i^n)}{\Delta x} \quad , \\ \frac{\partial f}{\partial t} &= \frac{1}{2} \frac{(f_{i+1}^{n+1} - f_i^{n+1})}{\Delta t} + (1-\theta) \frac{(f_{i+1}^n - f_i^n)}{\Delta t} \end{aligned} \quad (3)$$

With:

- i : Space step
- n : Time step
- θ : Weighting coefficient

4. THE LINEAR SYSTEM

After discretization, the Barré de Saint Venant equations are linearized around a reference state in order to design an approximate linear model of the true system in state space form [5]:

$$\begin{cases} X_{k+1} = A \cdot X_k + B \cdot U_k + B_p U_p, \\ Y_k = C \cdot X_k \end{cases} \quad (4)$$

Where

- A: state transition model
- B: control-input model
- C: observation model

These matrices are real constant matrices of appropriate dimensions.

The X state vector is composed of hydraulic variables (discharges Q and water levels Z) at each calculation cross section, relative to a reference state (δ variables) (5):

$$X = \begin{pmatrix} \delta Q_1 \\ \delta Z_1 \\ \delta Q_2 \\ \delta Z_2 \\ \vdots \\ \vdots \\ \delta Q_n \\ \delta Z_n \end{pmatrix}, \quad (5)$$

5. THE KALMAN FILTER

5.1 The uncertainties on the linear system

In practice, a linear model is not a perfect representation of the reality and the inputs and the measurements are not perfectly precise. There are some uncertainties on the model, on the inputs and on the measurements. This is the reason why noise is added to the process model and to the measurements, in order to better represent a realistic system, when used to generate data in a twin experiment framework. The linear stochastic difference equations become (6):

$$\begin{cases} X_{k+1} = A \cdot X_k + B \cdot U_k + B_p U_p + w_k, \\ Y_k = C \cdot X_k + v_k \end{cases} \quad (6)$$

The random variables w_k and v_k are assumed to be independent to each other. They are considered like white noises, and with normal probability distributions:

$$P(w) \sim N(0, Q), \quad (7)$$

$$P(v) \sim N(0, R), \quad (8)$$

The Q and R matrices can be time varying. In our simulations we took these matrices as time invariant and diagonal (9):

$$Q = \begin{pmatrix} \sigma_Q & 0 & \dots & \dots & \dots & \dots & \dots & 0 \\ 0 & \sigma_Z & \dots & \dots & \dots & \dots & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & \dots & \dots & \dots & \dots & \sigma_Q & 0 \\ & & & & & & 0 & \sigma_Z \end{pmatrix}; R = \begin{pmatrix} \sigma & 0 & \dots & \dots & \dots & \dots & \dots & 0 \\ 0 & \sigma & \dots & \dots & \dots & \dots & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & \dots & \dots & \dots & \dots & \sigma & 0 \\ & & & & & & 0 & \sigma \end{pmatrix}, \quad (9)$$

5.2 Kalman filter equations

The equations for the Kalman Filter are divided into two groups: time update equations and measurement update equations. The time update equations project forward in time the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations incorporate new measurements into the a priori estimate to obtain an improved a posteriori estimate.

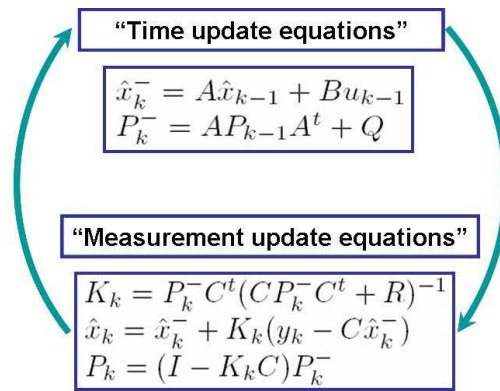


Figure 3: Kalman filter equations

These equations are simple matrix calculations, requiring little CPU time even for 300×300 matrices. The calculation can even be further reduced by using the asymptotic K_k matrix (obtained solving a Riccati equation) without loss of performance (this has been tested and verified, but not presented in this paper).

6. TESTS

A Kalman Filter is first used to reconstruct unmeasured data on three scenarios, representative of real field problems. In these scenarios twin experiments are conducted. The first simulation is used to generate data. White noises are then added to them to simulate uncertainties on the model and on the measurements. The second simulation is then done using the Kalman filter to reconstruct data and detect faults.

Hypotheses

- Time step for the simulations is 300 seconds.
- The upstream hydropower plant is on operation. That means there are discharge variations of 100 m³/s around an initial value of 1683m³/s. The other inflows are supposed to remain constant during the simulation: 10m³/s at Charmes dam, 1m³/s at Eyrieux, 5m³/s at Drôme, 1m³/s at Ouvèze, 999m³/s at Logis-Neuf downstream power plant and 701m³/s at Pouzin dam.
- The initial state is null (+ white noise).
- For the matrix Q, we choose $\sigma_Q = 2\text{m}^3/\text{s}$, $\sigma_Z = 0.001\text{m}$. For the matrix R, we choose $\sigma = 0.02\text{m}$.
- There are 8 water level measurements (y_1, y_2, \dots, y_8)

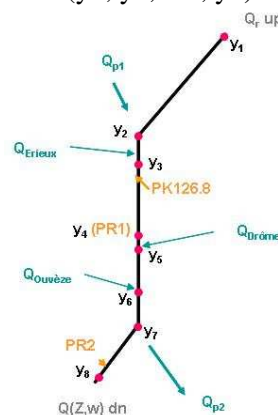


Figure 4: Inputs, outputs and measurements on the studied system

6.1 The first scenario

In this scenario we suppose that the water level sensor at location PR1 (Fig. 4) has a drift of 7cm from time 4h to 10h. We can see (Fig. 5-6) that the re-estimation state at the sensor location is very close to the real value, despite the wrong measurement. The high frequencies changes on the graphs are due to the white noise added to the measurements to simulate the uncertainties on the measurements. This sensor can then be detected as in default, and removed from the Kalman filter inputs. We observed in this case that the state reconstruction is even slightly improved.

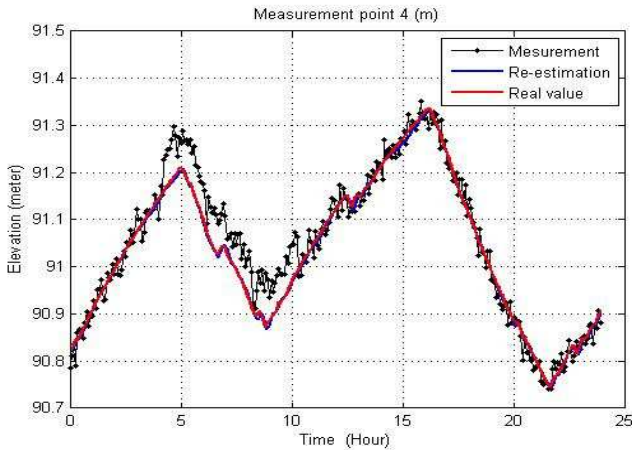


Figure 5 : State estimation at sensor location

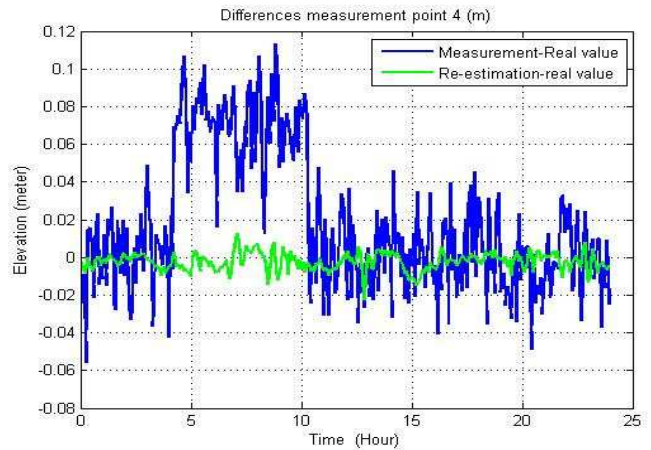


Figure 6 : State estimation error at sensor location

6.2 The second scenario

The second scenario aims at reconstructing unknown inflows at Eyrieux and Ouvèze tributaries, along with all the states of the system. We can observe (Fig. 7-8) that the inflows are correctly reconstructed. First, we tested the Kalman filter with all the 8 water level measurements. Then we tested with only 2 measurements: upstream (y1) and downstream (y8) of the development scheme. We can see the uncertainties on the measurements and on the model do not disturb the reconstruction of the unknown inflow by the Kalman filter even if just two measurements are taken into account. The filter can determine the value and time of the discharge of the unknown tributaries.

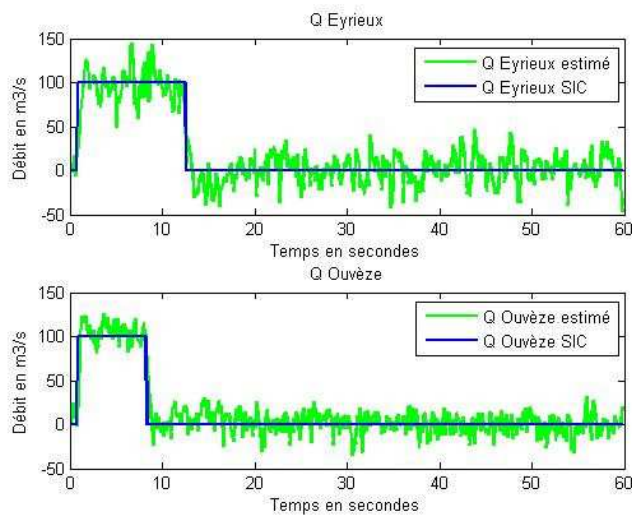


Figure 7 : State estimation with 8 measurements

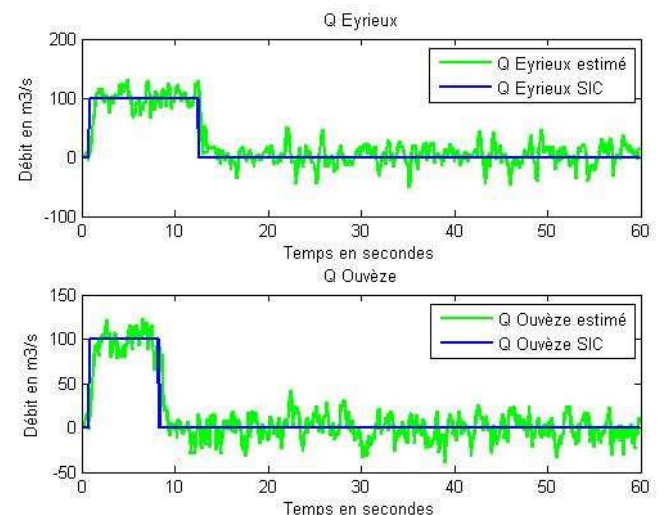


Figure 8 : State estimation with 2 measurements

6.3 The third scenario

This scenario using real data aims at reconstructing unknown upstream flows following sensors breakdowns. This is a realistic scenario, since even though most sensors are redundant on the Rhône River, they can have

simultaneous failures. This event really happened on the field in March 2009. We can observe that the missing discharge measurement at the upstream power plant is correctly reconstructed along with the water measurements at PK126.8, PR1 and PR2 (Fig 4).

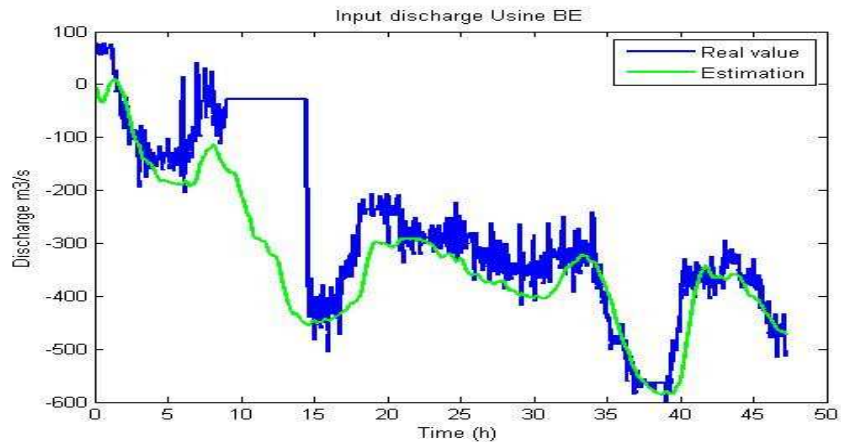


Figure 9: Real case, faulty sensor at upstream plant

CONCLUSIONS

In this paper, we have proposed a way to estimate, in real time, the hydraulic state of a river reach from measurements. The uncertainties on the model, on the inputs and on the measurements are correctly taken into account, detected and corrected by the Kalman filter. With this result, these errors will not disturb the automatic control of the development scheme. This knowledge of the hydraulic state, despite different sources of uncertainties and errors is of first importance in the current context of more demanding water resources management.

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