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Data Assimilation in Water Distribution Systems

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Abstract

Operational management of water distribution networks (WDNs) requires assimilating observations such as pressures at junction nodes, flows in pipes and, whenever available, monitored demand.
Although several data assimilation techniques are today available, ranging from 1-2-3-4 DVAR to Kalman Filters, a problem is posed by the need of preserving the structural relations among state variables in a WDN, such as for instance pressure head, discharge and demand.
Ensemble Kalman Filters certainly can be used to account for non-linearities but, for example, if one tries to assimilate pressure heads and pipe flows at the same time, nothing guarantees that the resulting variables after the data assimilation step, will still obey to the hydraulic structural relations mathematically describing a WDN.
In this work an EnKF based procedure has been implemented, which allows to assimilate three types of observations, namely pressures at junction nodes, flows in pipes and monitored demand.
The procedure allows to assimilating all the observations in three successive steps, while guaranteeing the full satisfaction of the structural relations.
The results, demonstrated over an operational network, show the high performance of the chosen approach.

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Keywords: Water Distribution Systems; Data Assimilation; Kalman Filters; Ensemble Kalman Filters.

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1. Introduction

The operational management of a water distribution network requires the availability of a reliable and properly calibrated hydraulic model of the network. It is thus necessary to set up a measurement network that allows to assimilate nodal pressures, pipe flows and, whenever available, demand measures.

Nomenclature

$\mathbf{H}$	nodal pressure heads vector
$\mathbf{H_0}$	known nodal pressure heads vector
$\mathbf{Q}$	pipe flows vector
$\mathbf{d}$	nodal demands vector
$\mathbf{d}_j$	nodal demands ensemble based on prior assumptions
$\mathbf{H}_{\vert\mathbf{d}_j}, \mathbf{Q}_{\vert\mathbf{d}_j}$	the value of state vectors $\mathbf{H}$ and $\mathbf{Q}$ given $\mathbf{d}_j$
$\mathbf{H}_{\vert\mathbf{d}_j,\mathbf{z}_H}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H}, \mathbf{d}_{\vert\mathbf{d}_j,\mathbf{z}_H}$	the value of state vectors $\mathbf{H}$, $\mathbf{Q}$ and $\mathbf{d}$ given $\mathbf{d}_j$ and measures $\mathbf{z}_H$
$\mathbf{H}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q}, \mathbf{d}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q}$	the value of state vectors $\mathbf{H}$, $\mathbf{Q}$ and $\mathbf{d}$ given $\mathbf{d}_j$ and measures $\mathbf{z}_H$ and $\mathbf{z}_Q$
$\mathbf{H}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q,\mathbf{z}_d}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q,\mathbf{z}_d}, \mathbf{d}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q,\mathbf{z}_d}$	the value of state vectors $\mathbf{H}$, $\mathbf{Q}$ and $\mathbf{d}$ given $\mathbf{d}_j$ and measures $\mathbf{z}_H$, $\mathbf{z}_Q$ and $\mathbf{z}_d$
$\mathbf{A}_{11}$	diagonal matrix defined as in [1]
$\mathbf{A}_{12}$, $\mathbf{A}_{21}$, $\mathbf{A}_{10}$	(0,1) topological incidence matrices defined as in [1]
$\boldsymbol{\mu}_H, \boldsymbol{\mu}_Q, \boldsymbol{\mu}'_Q$	vectors of means of $\mathbf{H}_{\vert\mathbf{d}_j}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q}$ estimation errors
$\mathbf{P}_H, \mathbf{P}_Q, \mathbf{P}'_Q$	variance-covariance matrices of $\mathbf{H}_{\vert\mathbf{d}_j}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q}$ estimation errors
$\mathbf{K}_H, \mathbf{K}_Q, \mathbf{K}'_Q$	Kalman Gain matrices for state vectors $\mathbf{H}_{\vert\mathbf{d}_j}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H}, \mathbf{Q}_{\vert\mathbf{d}_j,\mathbf{z}_H,\mathbf{z}_Q}$
$\mathbf{z}_H, \mathbf{z}_Q, \mathbf{z}_d$	vectors of measurements relevant to state vectors $\mathbf{H}$, $\mathbf{Q}$ and $\mathbf{d}$
$\mathbf{M}_H$, $\mathbf{M}_Q$, $\mathbf{M}_d$	(0,1) topological matrices relating $\mathbf{z}_H$ to $\mathbf{H}$, $\mathbf{z}_Q$ to $\mathbf{Q}$ and $\mathbf{z}_d$ to $\mathbf{d}$
$\bar{\mathbf{v}}_{\mathbf{z}_H}, \bar{\mathbf{v}}_{\mathbf{z}_Q}, \bar{\mathbf{v}}_{\mathbf{z}_d}$	vectors of means of measurement errors for state vectors $\mathbf{H}$, $\mathbf{Q}$ and $\mathbf{d}$
$\mathbf{R}_{\mathbf{z}_H}, \mathbf{R}_{\mathbf{z}_Q}, \mathbf{R}_{\mathbf{z}_d}$	variance-covariance matrices of measurement errors for state vectors $\mathbf{H}$, $\mathbf{Q}$ and $\mathbf{d}$

Among the established techniques for assimilating observations [2], the Ensemble Kalman Filter (EnKF) [3], allows taking into account the non-linearity of the structural models in state extrapolation, but when using state vectors comprising simultaneously flows and pressures, the fulfillment of the structural hydraulic relations among the state variables cannot be guaranteed at the end of the data assimilation phase. In this work, it is instead presented a technique of successive conditionings, in a cascade of three EnKFs, which allows assimilating the various types of observations (pressures, flow rates and demands) while ensuring the preservation of the structural links among the resulting variables [4].

2. The proposed data assimilation procedure

To start the assimilation process using an EnKF, as in any Bayesian inferential process [5], prior knowledge is described via an appropriate probability distribution. Therefore, our prior knowledge on demands, which are scarcely known in a WDN, is assumed to be described for all the nodes by a log-normal probability distribution with mean $\boldsymbol{\mu}_{d_i}$ and variance $\boldsymbol{\sigma}^2_{d_i}$ where d_i, with $i \in \{1, \dots, n\}$, represents the demand at node i, while n is the number of nodes of the network. Demands at all nodes can be set into a state vector $\mathbf{d}$ of size n.

The assimilation process then begins with the generation an "ensemble" of m members of nodal demands, namely $\mathbf{d}_j$, with $j \in \{1, \dots, m\}$, using the assumed prior distributions. The size of the ensemble must be large enough to ensure that the matrices involved in the assimilation phase, and defined below, are invertible. Each ensemble