

## An integrated state estimation approach to enhance the on-line monitoring capabilities of water distribution systems

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### ABSTRACT

*State estimation techniques have been widely discussed in academia in the context of water distribution systems, but there are few real-life applications. The aim of this paper is to show the potential advantages of systematically implementing state estimation techniques for on-line monitoring water distribution systems. With this purpose, two state estimation-based methodologies are here applied to C-Town case study: (1) calibration via multi-period state estimation, in order to adjust model parameters based on state estimation results over time, and (2) topological state estimation, in order to identify changes in the statuses of pumps and valves. Results show that state estimation techniques are a good alternative to adapt the paradigm of water distribution networks analysis to the reality of telemetry systems.*

**Keywords:** ICT, calibration, topological analysis.

## 1 INTRODUCTION

State estimation techniques are efficient tools to infer the most likely hydraulic state of any water distribution network (i.e. head levels, demands and flows) from the available measurements provided by a telemetry system. This information can in turn be used to provide a better quality supply service, and for this reason state estimation has attracted the attention of the water sector since the 1980s [1]. State estimation techniques have been widely discussed on a scientific level in water systems (see [2] for references), but the truth is that only few real-life water network applications exist (e.g. [3,4]). This may be due to the fact that: (1) water systems have traditionally lacked of metering devices, (2) other complementary analysis required to take full advantage of SE results (e.g. observability analysis, uncertainty evaluation) have not been consistently addressed in the water domain, and (3) specific water distribution systems applications, such as calibration or topological analysis have evolved as independent problems rather than as part of the state estimation process. Similarly, calibration tools have been widely discussed in academia, but they are not used much in practice [5].

This situation contrasts with the current advances in *Information Communication Technologies* (ICT) and proves that such platforms are being underused. Now that a significant number of metering devices and supervisory control and data acquisition (SCADA) platforms are being installed, it is high time that water distribution systems take full advantage of telemetry systems by embracing state estimation procedures. The objective of this paper is to show the potential advantages of systematically implementing state estimation techniques for on-line monitoring water distribution systems. With this purpose, calibration and topological analysis problems are here

addressed from a state estimation perspective to highlight the importance of adopting a common view for on-line control purposes. Note that up to this date, these problems have been mostly tackled individually, but in order to make the most of telemetry systems, a unified comprehensive approach to the on-line reality of water networks is required.

To begin with, calibration strategies have been typically conceived as simulation-based approaches, which use a hydraulic model as the engine for parameter adjustment instead of using a formal state estimation approach [6]. However, these procedures do not take into account that all telemetry measurements could eventually fail and are subjected to noise. For this reason, they have recently been reported as inappropriate for on-line control purposes [7]. [6] has resumed the combined parameter and state estimation problem in order to infer both the hydraulic state and model parameters from the available measurements. However, consideration of multiple time periods, which is desirable to adjust the hydraulic model based on information about the system over time, is still associated with a great computational complexity.

Similarly, topological issues have been discussed in the context of solving (e.g. [8]) and calibrating (e.g. [9]) water networks, but not within state estimation. Topological state estimation is conceived to infer not only the hydraulic state of the system but also the status of the pumps and valves within the system from the available measurements. Note that existing state estimation procedures up to this date assume a given network topology, which may not correspond to the reality of the system if unnotified changes in operation have taken place. Such possibility has been recently studied with the so called topological observability analysis [10]. Nevertheless, observability analysis only enables to assess if sufficient relationships exist, and the topological state estimation problem itself must be addressed to consider measurement noise for pump and valve status determination.

This paper is organized as follows. Firstly, the methodologies here adopted to address the calibration and topological issues from a state estimation perspective are briefly outlined. Then, results for both applications are obtained for C-Town case study, which is an illustrative example widely used in the technical literature. Finally, relevant conclusions are duly drawn. Note that these methodologies are particular contributions of [11], and therefore a more complete overview of the approach and specific details about the methods here used can be found in that document.

## **2 METHODS**

In this section, the methods here adopted to solve the calibration problem and the topological state estimation issue are briefly outlined.

### **2.1 Calibration via multi-period state estimation**

As explained in the Introduction, there is a current trend to address the calibration problem from a state estimation perspective [6]. It is important to highlight that the state estimation problem has traditionally assumed that the water system has been previously calibrated [12], i.e. state estimation assumes that model parameters are known and infers the hydraulic variables of the system from the available measurements. But model parameters change over time, and it is advisable to reassess them every now and then to make sure that the hydraulic model correctly represents the real system. From a state estimation perspective, this implies that both the hydraulic variables and the parameters of the system must be inferred from the available measurements, leading to an increase in the computational complexity of the optimization problem. This is especially true if more than one time period is taken into account to calibrate the system, which is always desirable [13].

In this work, the multi-period parameter and state estimation problem is addressed with mathematical programming decomposition techniques. This approach starts the calibration process from several state estimation results at different times for a given roughness value, which are here called *subproblems*. Note that roughness coefficients are here taken as the only model parameters, as done before by many others (e.g. [14], [6]). Then, the sensitivity of the objective function with respect to roughness coefficients is computed for each of those subproblems with finite differences, i.e. perturbing the state estimation solution around the optimum. Based on the sum of these sensitivities, a new estimation of the roughness value can be obtained in a subsequent stage called the *master problem*. Decomposition techniques have traditionally been implemented as recursive procedures, but in this work the computation of first-order derivatives is integrated in a quasi-Newton method to speed the process. More details about the methodology can be found in [15].

## 2.2 Topological state estimation

Even though calibration has been a matter of extensive research over the last decades, the real problem when estimating the state of the system is normally to determine changes in the network topology, which are here considered as changes in the pump and/or valve status. For this reason, current research is focusing on integrating changes of operation in the calibration process (e.g. [16], [17]). In this work, topological state estimation is presented as a procedure that enables to infer not only the hydraulic state of the system but also the statuses of pumps and valves from the available on-line data. Therefore, this approach enables to detect changes in the pump and/or valve operation with respect to the previously calibrated model. Note that for this application, we assume that model parameters have been previously calibrated, because given the current availability of metering devices in real systems, at present it is unfeasible to infer also roughness coefficients in the process.

The possibility of all pumps and valves being opened or closed is included in the state estimation formulation by means of binary variables, which lead to a mixed integer non-linear programming problem. Given the current state of the art for optimization solvers, it is not possible to develop a robust solution for such type of problems, so in this work we adopt the mixed integer quadratic programming approach developed by [18]. This approach linearizes the non-linear equations of the problem (i.e. Hazen-Williams and characteristic curves for pumps and valves) through an iterative process. Moreover, the methodology enables to consider that the characteristic curve of pumps and valves may or may not be known. This is important since in many real systems there is no detailed information about such devices.

## 3 RESULTS

As the main objective of this work is to demonstrate the potential of state estimation techniques to take full advantage of available measurements in water supply systems, this section presents the results obtained with the aforementioned methodologies for C-Town case study. The C-Town network was firstly presented in the so called “Battle of Background Leakage Assessment for water networks” [19]. The original system presented 1 reservoir, 7 tanks, 388 nodes, 432 pipes, 11 pumps (grouped in 5 pumping stations here called P1, P2, P3, P4 and P5), 1 gate valve, and 1 check valve. In this work, terminal nodes with null demands (and their associated pipes) have been removed, because these regions are subjected to null flow and they imply an additional computational expense that is not required. Figure 1 shows the resulting system layout, where the roughness value is also represented. Note that the Hazen-Williams roughness coefficients proposed in the original problem are here modified in order to work with only 4 groups of pipes:  $C_{g,real} = [70, 90, 110, 130]$ .

Therefore, the roughness of each pipe is approximated to the closest group roughness value. This implies a considerable reduction in the complexity of the problem with view to calibration.

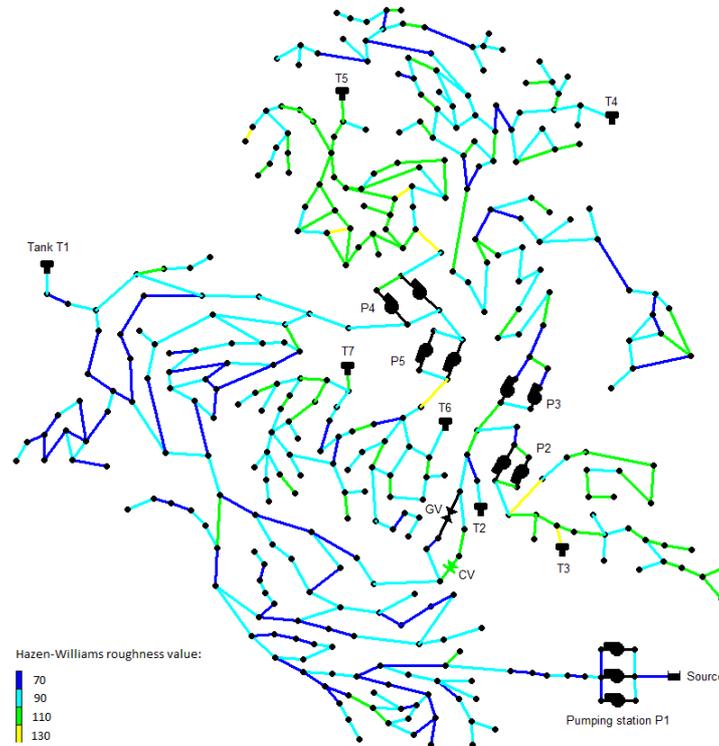


Figure 1. C-Town case study: Hazen-Williams roughness coefficients

In what regards the available information, measurements are synthetically generated in this work to check the performance of the algorithms when applied to C-Town case study. More specifically, it is here assumed that water levels at the reservoir and tank nodes are metered, and so are the water flows at all the pipes that come out of the sources to the system (eight pipes). Also, water demands are *pseudomeasured*, i.e. estimated based on historical data, at all nodes. The standard deviations considered for each type of measurement are 0.01 m for water level meters, 2% the flow value for flow meters and 20% the demand value for demand pseudomeasurements. This is reasonably close to what can be typically found in real water supply systems.

### 3.1 Calibration via multi-period state estimation

One of the key aspects of the calibration methodology outlined in this paper is to start from several state estimation results over time. In this regard, 24 measurement configurations are considered in this paper, one at each hour during a day. As mentioned before, each of these measurements is synthetically generated with the standard deviations previously presented. Table 1 provides the calibration results considering two starting points in order to assess the performance of the algorithm: (1) considering the starting point equal to 90% the real roughness value for each group (i.e.  $C_{g,0} = [63, 81, 99, 117]$ ), and (2) considering the initial roughness values equal to 100 in all pipes ( $C_{g,0} = [100, 100, 100, 100]$ ).

*Table 1. Calibration via multi-period state estimation results for C-Town case study*

	$C_{g,real}$	$C_{g,estim}$	$J_{estim}$	$n_{eval}$	t (s)
$C_{g,0} = 63$	70	69.6582	185.9628	34	6671.00
81	90	89.6163			
99	110	108.4727			
117	130	129.5980			
$C_{g,0} = 100$	70	69.6578	185.9628	31	6259.30
100	90	89.6166			
100	110	108.4718			
100	130	129.5986			

This table provides information about the estimated roughness values ( $C_{g,estim}$ ), the objective function of the optimization problem for such values ( $J_{estim}$ ), the number of function evaluations required to attain the solution ( $n_{eval}$ ) and the computational time (t) required for the algorithm to converge on a desktop computer. As Table 2 shows, the estimated roughness value is practically the same for both initializations, and so is the value of the objective function at the optimum, i.e. the algorithm converges well no matter the starting point. Note that the objective function does not reach a null value because of the noisy nature of measurements, and for this reason the estimated values do not exactly correspond to  $C_{g,real}$ . Moreover, the initialization seems to have no impact on the computational time, as it takes roughly 100-110 minutes for the method to find the correct solution. This is due to the fact that the sensitivity of the state estimation solution is used to update roughness values, speeding the search process. In any case, it must be highlighted that this computational time is not suitable for on-line applications. Note that the calibration approach here presented is intended to readjust roughness parameters off-line from previously available state estimation results. Therefore, the methodology contributes to keep an up-to-date model of the system and should be run from time to time (e.g. every week or month).

### 3.2 Topological state estimation

This methodology is here applied to one single time period, as its aim is to on-line estimate the hydraulic state and the statuses of pumps and valves in the network based on the previously calibrated model. For this reason, we consider at this point the steady state of the network, neglecting the demand patterns and controls provided when the C-Town problem was first posed for leakage detection purposes. Then, 1000 measurements are here generated around the flow network solution to assess the effect of measurement noise through a sampling experiment (i.e. Monte Carlo method): the topological state estimation algorithm is solved for each of the 1000 measurement settings to assess the percentage of success in determining the statuses of the pumps and valves in the system. Note that the algorithm is expected to identify the correct pump and valve status (all pumps working, gate valve opened and check valve closed) even with measurement noise.

Table 2 provides the results of the 1000 Monte Carlo simulation when considering that the characteristic curves of all the pumps in the system are known. As all pumps in the same station

have equal characteristic curves, this table gathers the percentage of success in determining the number of pumps working in each pumping station  $i$  ( $S_{P,i}$ ), the percentage of success in determining the status of the gate valve ( $S_{GV}$ ) and the check valve ( $S_{CV}$ ), the mean ( $it_m$ ) and maximum ( $it_{max}$ ) number of iterations required for the problem to converge, the mean squared error of flows (MSE), and the mean time required to run the algorithm for each simulation on a desktop computer ( $t_{mean}$ ). To begin with, this table shows that the percentage of success in determining the number of pumps working per pump station is 100%, and so are the percentages of success in determining the gate valve and check valve statuses. This is due to the fact that even though measurements are noisy, the available information is enough to correctly determine the pump and valve statuses in all Monte Carlo simulations. Note that this may not be the case if some measurements fail (e.g. sensor failure, communication failure), as the topological observability of the system may be compromised. As a matter of fact, if the characteristic curves of all the pumps in the system were unknown instead of known (e.g. if their information was lost) the system would become topologically unobservable, and therefore state estimation results would not be reliable. This could be identified by applying the topological observability analysis described in [10] as a systematic prior step to the topological state estimation process here presented. For this reason, some water utilities are already working on assessing the observability of their networks under different scenarios [20]. However, it must be highlighted that the effect of measurement noise can only be assessed with a proper topological state estimation, as observable variables may eventually lead to wrong status determination as a result of measurement noise [10].

*Table 2. Topological state estimation results for C-Town case study*

$S_{P,1}$ (%)	100
$S_{P,2}$ (%)	100
$S_{P,3}$ (%)	100
$S_{P,4}$ (%)	100
$S_{P,5}$ (%)	100
$S_{GV}$ (%)	100
$S_{CV}$ (%)	100
$it_m$	3.9980
$it_{max}$	5
MSE ( $m^6/h^2$ )	1.7431
$t_{mean}$ (s)	4.22

Also, Table 2 shows that the mixed integer quadratic programming approach adopted in this paper is quite stable, with a mean number of iterations of 4 and a maximum value of 5. This is due to the fact that the problem is initialized relatively close to the optimum, but as in the calibration approach, the algorithm does not seem to be highly burdened by the initialization [18]. Finally, the mean squared error is reasonably low, and the mean time required to run the algorithm is around 4 seconds, thus the method seems suitable for its real-time implementation.

## 4 CONCLUSIONS

This work intends to show the potential of embracing a state estimation approach to address the on-line monitoring problem in all its complexity. With this aim, a methodology for calibrating the system via multi-period state estimation and a method for topological state estimation are here outlined. The calibration approach is here presented as an off-line application that enables to readjust the roughness values for the pipes in the system from several state estimation results over time, assuming a given network topology. Then, topological state estimation is used to infer in real time the hydraulic state and the statuses of the pumps and valves in the system, i.e. to detect changes in the operation of the previously calibrated hydraulic model. Results show that both calibration and topological state estimation applications work well and are essential to keep an up-to-date model of the system, and this is the first necessary step to adequately simulate the real water network behaviour. Therefore, the state estimation framework seems to be an appropriate basis on which other applications, such as leak detection, sampling design or optimal operation schemes can be built. This is a subject for further research.

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