EPiC Series in Engineering
Volume 3, 2018, Pages 698–705
HIC 2018. 13th International Conference on Hydroinformatics

Real-time measurement fault detection and remote-control in a mountain water supply system

Sofia Fellini[1*], Riccardo Vesipa[1], Fulvio Boano[1] and Luca Ridolfi[1]

[1] Dept. of Environment, Land and Infrastructure Engineering,
Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Turin, Italy
sofia.fellini@polito.it

Abstract

This work presents an algorithm for real-time fault detection in the SCADA system of a modern water supply system (WSS) in an Italian Alpine Valley. By means of both hardware and analytical redundancy, the proposed algorithm compares data and isolates faults on sensors through the residual analysis. Moreover, the algorithm performs a real-time selection of the most reliable measurements for the automated control of the WSS operations. A coupled model of the hydraulic and remote-control system was developed to test the effectiveness of the proposed algorithm. Simulations showed that error detection and measurement assessment are crucial for the safe operation of the WSS.

1 Introduction

In mountain regions, water supply (WS) to the local communities is usually provided by municipal water supply systems (WSSs) that rely on local sources and operate independently from each other. In the event of unexpected breakdowns or droughts (Carrera, et al., 2013), this fragmentation results in inefficiencies and water crisis. In order to increase the resilience of the WS service, a growing trend is the creation of inter-municipal water networks that connect multiple local WSSs (Massarutto, 2000). Coordination in the operations of multiple WSSs and diversification of water sources result in economic, environmental and water quality advantages (Bel & Warner, 2015; Anghileri, et al., 2012). These modern WSSs require an automated regulation aimed to control the operations of the entire water infrastructure, according to a centralized control perspective. For this reason, they are managed by SCADA (Supervisory Control and Data Acquisition) systems (Meseguer & Quevedo, 2017; Coelho & Andrade-Campos, 2014) that (i) provide real-time pressure and flow rate measurements in the key

[*] Created the first stable version of this document

points of the network and (ii) remotely control the operations of the control devices (e.g., valves, pumps, turbines), according to predefined management rules and to the data measured in real-time throughout the system.

In this framework, lack of data or errors in the sensors may result in a misleading regulation and in malfunctions in the WSS operations. Therefore, it is important to equip the control systems with procedures that can detect errors in sensors. Fault detection and isolation (FDI) methods have been proposed in different fields of control engineering, like in industrial plants (e.g., Gertler, 1988; Özyurt & Pike, 2004) and in the automotive and aerospace engineering (Chen & Patton, 2012). However, few applications have been done for the validation of measurements in water networks (e.g., Ragot & Maquin, 2006).

Fault diagnosis is generally based on redundancy that can be either hardware redundancy or analytical redundancy (Hwang, et al., 2010; Gertler, 2015). In hardware redundancy, measurements of the same signal generated by various sensors are compared. On the other hand, analytical redundancy uses a mathematical model of the system as a comparison term (Isermann, 2005). In both methods, fault detection involves two steps: (i) residual generation and (ii) residual evaluation. A residual is a signal that is zero when the system is operating correctly and non-zero when faults are present.

The goal of this paper is to present an algorithm for faults detection in the SCADA system of a modern WSS (Fellini, et al., 2017). The WSS is located in an Alpine valley in northwestern Italy and consists of an 80-km-long water main connecting 20 municipal WSSs (Figure 1). The water main takes water from a high-altitude reservoir, connects the municipal tanks and provides additional water when needed. Moreover, there are four inline tanks along the water main, and the excess water pressure is converted into hydropower by three turbines. Flow adjustments through turbines and valves are remotely controlled by a SCADA system (Fellini, et al., 2017).

In order to increase the safety and the reliability of the control system, an algorithm for the real-time detection of measurement faults has been developed. By a residual analysis, redundant measurements are compared and faults are automatically detected. Moreover, in case of errors, the developed algorithm ensures continuity in the control operations and prevents interruptions in the water supply. A numerical model of the hydraulic and control operations of the WSS is used to assess the developed algorithm.

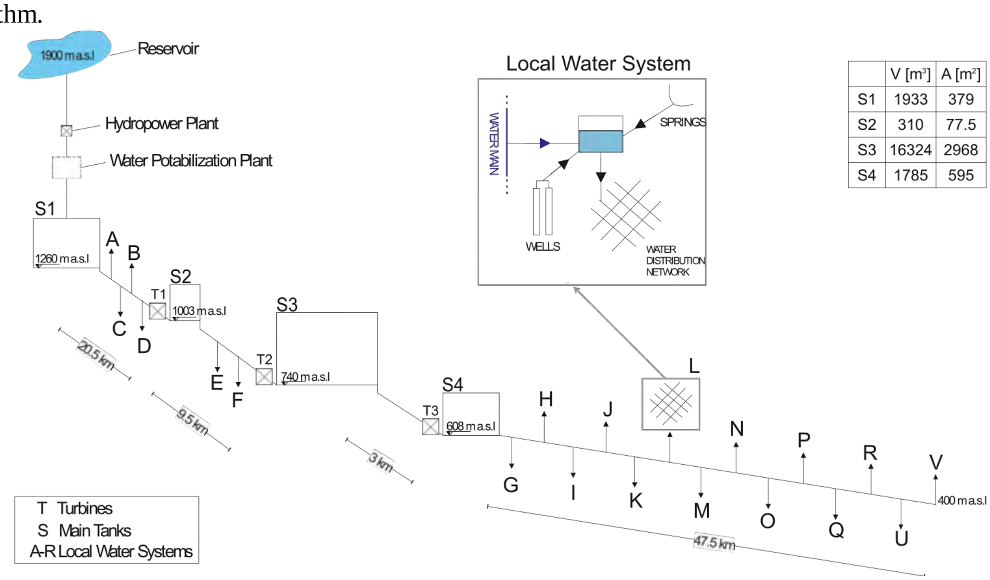

Figure 1: Scheme of the WSS. The capital letters (A, B,…) indicate the local water supply systems; the inset shows a typical local water system with a storage tank supplied by mountain springs, local wells, and the new water main.

2 Case study

The case study was previously described in (Fellini, et al., 2017) and involves a modern WSS (Figure 1). A water main collects high quality water from an alpine reservoir and supplies the municipal WSSs (A to V in Figure 1). Needle valves with electronic actuators regulate the flow delivered from the water main to the local tanks. Four inline tanks (S_1, S_2, S_3 and S_4) split the water main in order to limit the static water pressure in the pipes. A Pelton turbine with electronically controlled Doble needles adjusts the flow entering in each inline tank. Valves and turbines are thus the active elements that regulate the flow rate in the entire WSS. Local PLCs (Programmable Logic Controller) control these devices according to (i) predefined management rules, (ii) flow and level data measured by local sensors, and (iii) information and data received from distant devices networked in the SCADA system. Data transmission in the SCADA system is guaranteed by a redundant optical fibre network.

The management rules of the active devices were developed to optimize water distribution and to maximize the hydropower generation and the energy saving in the whole valley (Fellini, et al., 2017). In particular, flow adjustment through the turbines is aimed at (i) maintaining the water level in the inline tanks between predefined level thresholds and (ii) minimizing the number of turbine operations. Flow regulation through the needle valves is performed to optimize the distribution of water to the municipalities.

3 Methods

A simulation model was developed to analyse the performances of the WSS in different scenarios. This model consists of a coupled hydraulic and control model (section 3.1). Simulations (Fellini, et al., 2017) have shown that, by means of the operating rules implemented in the SCADA system, a comprehensive and optimal regulation of the WSS can be achieved. However, this control system fails when faulty data are measured and transmitted. For this reason, an algorithm for fault detection is developed (section 3.2).

3.1 The hydraulic and control model

The hydraulic model is a system of non-linear equations describing (i) the flow-head loss relation in pipes, at valves and at turbines, (ii) the flow continuity at nodes and (iii) the boundary conditions at tanks. Time evolution of the system is modelled by a succession of steady states with duration Δt. At each time step flow in the pipes and pressure at the nodes of the WSS are computed. Moreover, water level in tanks is updated using a mass balance equation.

The control model simulates the supervision and control operations of the SCADA system. A real measurement from a generic sensor is simulated as $m=M+\varepsilon$, where M is the flow or pressure datum computed by the hydraulic model. This datum is perturbed with an error ε to model different kinds of sensor failures (statistical errors, random oscillations, drifts and signal interruptions). This perturbed measurement is used as input for the decision algorithms that simulate the control operations of the SCADA system.

3.2 The algorithm for fault detection in sensors

A method for real-time fault detection in the above presented SCADA system is developed. This method is based on the redundancy concept and can be applied when several values of the same physical variable are available. Usually, critical sensors in a SCADA system are duplicated. This instrumental redundancy provides error detection in the event that the two sensors give different results but cannot automatically determine which sensor is faulty. Thus, a technician's on-site intervention is often the only solution. However, modern infrastructures require an automatic error correction to guarantee continuity in real-time control operations. A triple redundancy is thus required. In this case, if one of the three sensors fails, the other two sensors can correct and mask the fault. The algorithm we present detects sensor faults by comparing three values of the same measurement, provided by two redundant gauges (hardware redundancy) and an hydraulic equation (analytical redundancy). In this way, resilience is achieved and the expensive installation of three redundant sensors is avoided.

In details, the algorithm (step I in Figure 2) receives as input the three values A, B and C. A and B are transmitted by two redundant sensors, while C is obtained from an hydraulic equation. Residuals R_1, R_2 and R_3 are generated by calculating the difference between measurements two by two:

$$R_1=A-B, \quad R_2=B-C, \quad R_3=A-C. \tag{2}$$

Because of statistical errors in sensors (e.g., Fuller, 2009), the residuals are generally different from zero, even if there are no faults. Faults are detected by comparing each residual to its tolerance. The tolerance interval is determined in order to include statistical errors related to the instrumental precision:

$$tol_{R1}=tol_A+tol_B, \quad tol_{R2}=tol_B+tol_C, \quad tol_{R3}=tol_A+tol_C \tag{3}$$

where tol_A, tol_B and tol_C are the maximum instrumental errors for measurements A, B and C, respectively. If the *i-th* residual exceeds the tolerance, the *i-th* error variable switches to 1 (e.g., if $|R_1|>tol_{R1}$, $E_1=1$). When a sensor fails, two of the three error variables (E_1, E_2 and E_3) assume value equal to 1, since the error associated with a single measurement appears in the calculation of two residuals. As a consequence, the algorithm can automatically detect which is the faulty sensor (e.g., if R_1 and R_3 are out of tolerance, the sensor providing measurement A is identified as faulty).

Besides real-time error detection, the developed algorithm selects the most accurate data to be used in the control operations of the SCADA system (step II in Figure 2). For each measurement tern, the minimum residual is identified (M in Figure 2). The two measurements involved in the calculation of M are the closest to each other and therefore considered the most representative of the true value. The algorithm selects one (X in Figure 2) of these two measures for the control operations.

This last choice is based on technical considerations. Generally, priority is given to direct measures compared to indirect ones (i.e., measures from analytical models).

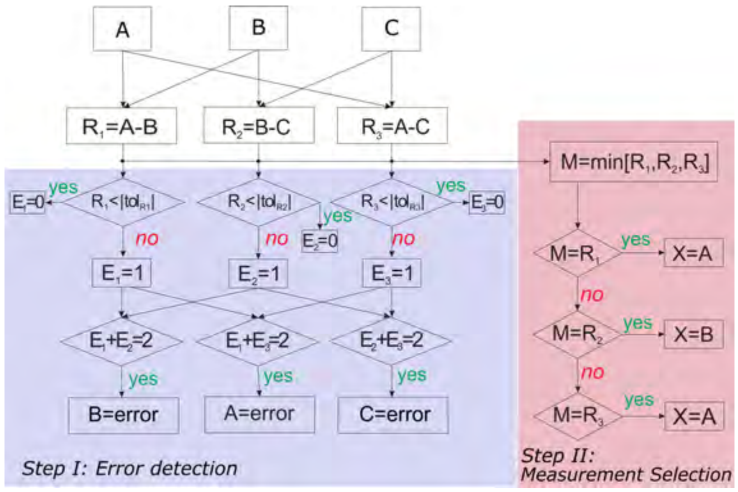

Figure 2: Algorithm for fault detection (Step I) in the WSS sensors and for the choice of the most reliable measurement (Step II) to be used in the control operations.

The above presented fault isolation procedure is effective if three values A, B and C of the same physical variable are available. In the WSS considered in this work, the key measurements for the control operations of the SCADA system are (i) level measurements in the inline tanks (S_1, S_2, S_3 and S_4 in Figure 1) and (ii) measurements of the flow rate towards the municipal WSSs (A to V in Figure 1). Regarding level measurements, each tank is equipped with two redundant level sensors (MH_1 and MH_2 in Figure 3a). Moreover, the tank level can be evaluated with a mass balance equation involving flow rate measurements into and out of the tank (MQ_{IN} and MQ_{OUT} in Figure 3a). Regarding flow rate measurements, two flow meters are installed along the pipes that supply each local WSS (MQ_1 and MQ_2 in Figure 3b). Furthermore, multiple flow meters intercept the water main (MQ_A and MQ_B in Figure 3b). Thus, a third value of the flow rate towards a local WSS can be evaluated with a flow rate balance equation.

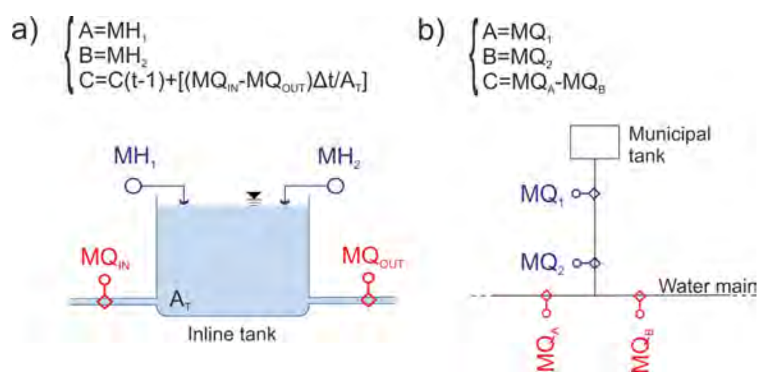

Figure 3: a) Level (MH_1 and MH_2) and flow rate (MQ_{IN} and MQ_{OUT}) sensors installed in an inline tank (with area A_T) of the WSS. The system of equations provides three redundant values (A, B and C) of the tank level. b) Flow rate sensors installed along the pipe that supply one of the municipal tanks (MQ_1 and MQ_2) and along the water main (MQ_A and MQ_B). The system of equations provides three redundant values (A, B and C) of the flow rate towards the municipal tank

4 Results and Discussion

The above presented algorithm for real-time fault detection and measurement selection was integrated in the control model of the WSS. First, the available gauges in the different districts of the WSS were located (hardware redundancy). Secondly, the balance equations that provide an additional value of the measured physical variables were identified (analytical redundancy). Thirdly, different types of error were simulated for the level and flow rate sensors installed in the WSS: (i) statistical errors, (ii) drifts, and (iii) critical gauge failures. Finally, simulations of the coupled hydraulic and decision model were performed.

In Figure 4 the algorithm for error detection is applied to level measurements at the inline tank S_1. As introduced in Figure 3a, two level sensors are installed in each inline tank (MH_1 and MH_2 in Figure 3a). A third value of the tank level was obtained using a mass balance equation of the flow rate into and out of the tank, measured at sensors MQ_{IN} and MQ_{OUT} (Figure 3a). In this simulation, all the measurements were disturbed by statistical errors related to instrumental accuracy. Statistical errors can be modelled as realizations of a Gaussian distribution with standard deviation equal to one third the maximum instrumental error (E_{max}). E_{max} was obtained from the technical specifications of the installed gauges and is equal to 1 cm for the level sensors, while it is equal to 0.25% of the flow rate for the flow meters. Figure 4c shows the effects of statistical errors on the three level measurements. Notice that, errors in the flow meters scarcely affect the precision of the level value obtained from the balance equation (magenta line in Figure 4c). Sensor MH_1 was further disturbed by drifts (1 in Figure 4a), random oscillations (4 in Figure 4a) and transmission interruptions (5 in Figure 4a). Moreover, the signal was set on the minimum (2 in Figure 4a) and full-scale (3 in Figure 4a) constant values to simulate critical failures of the sensor.

As shown in Figure 4a, the level measured by sensor MH_2 is almost equal to the value resulting from the balance equation. On the other hand, the level measured by MH_1 considerably differs from the previous ones, due to instrumental failures. By means of the residual analysis, the developed algorithm detects with high precision the presence of errors in the measurements transmitted by MH_1. In Figure 4b, for each level value, error detection is highlighted with a red signal. Moreover, the algorithm selects the most reliable measurement to be used in the control operations of the WSS in real-time (green signal in Figure 4b). Under ordinary conditions, the algorithm alternatively selects the data measured by the two level sensors MH_1 and MH_2. In case of error detection for MH_1, the measurement transmitted by MH_2 is the only one to be selected. In this way the algorithm guarantees resilience in the operations of the turbine T_1, whose regulation is based on the water level in tank S_1 (Fellini, et al., 2017). Similar results were obtained by applying the method to the other level and flow rate gauges in the WSS.

The developed algorithm is able to isolate errors only in the case of a single failure in the measurements involved in each system of three equations used for the residual analysis (e.g., equation systems in Figure 3a and Figure 3b). In the case of multiple simultaneous errors, the algorithm is not robust.

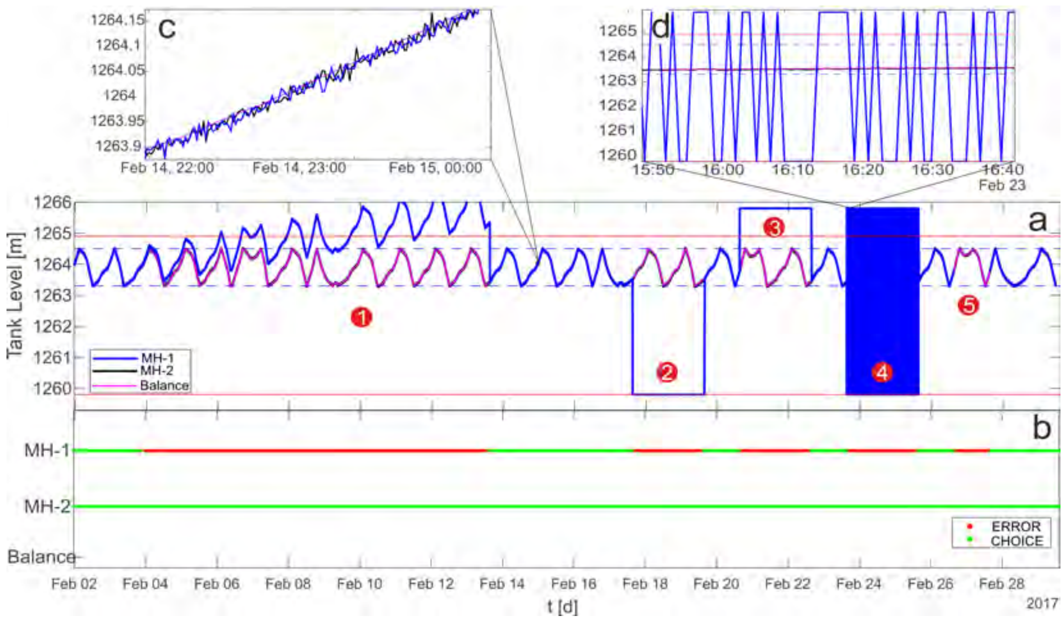

Figure 4: a) Level values from level gauges MH1 and MH2 and from a balance equation of flow rate into and out of the tank. The red lines are the maximum and minimum water level in tank. The blue dotted lines are the regulation thresholds (Fellini, et al., 2017). Measurements from MH1 experience drift (1), random oscillations (4), transmission interruption (5) and settle on the full-scale (3) and minimum (2) constant values. b) Error detection and measurement selection for the control operations in the WSS. c)-d) Measurement signals details.

5 Conclusions

In this work, an algorithm is proposed for real-time evaluation of data measured in the SCADA system of a modern WSS. The WSS faces multiple challenges: water supply over a large area, hydropower generation and coordination among multiple local water supply systems. Therefore, an automated remote-control system based on reliable flow rate and level measurements is crucial. The developed algorithm compares redundant data obtained from both redundant gauges and analytical models. By means of the residual analysis, failures and gross errors are detected in the considered measurements. Moreover, the algorithm performs a real-time selection of the most reliable measurements to be used in the control operations. The effectiveness of the method was assessed through numerical simulations of a coupled hydraulic and control model of the WSS. Results showed that high precision error detection is possible when a single failure occurs in the redundant measurements of the same physical variable. Moreover, the algorithm guarantees continuity in the operations of the WSS and the safety and the reliability of the system are increased. Further studies are required in the near future to extend the method to the case of simultaneous failures in redundant gauges.

Acknowledgments

We gratefully acknowledge SMAT Group for the financial support to this research and for providing valuable information.

References

Anghileri, D. et al., 2012. Optimizing watershed management by coordinated operation of storing facilities. *J. Water Resour. Plann. Manage., 139.5,* pp. 492-500.

Bel, G. & Warner, M. E., 2015. Inter-municipal cooperation and costs: Expectations and evidence. *Public Administration 93.1,* pp. 52-67.

Carrera, L., Mysiak, J. & Crimi, J., 2013. Droughts in Northern Italy: Taken by Surprise, Again. *Review of Environment, Energy and Economics (Re3).*

Chen, J. & Patton, R. J., 2012. *Robust model-based fault diagnosis for dynamic systems.* s.l.:Springer Science & Business Media (vol 3).

Coelho, B. & Andrade-Campos, A., 2014. Efficiency achievement in water supply systems-A review. *Renewable and Sustainable Energy Reviews, 30,* pp. 59-84.

Fellini, S., Vesipa, R., Boano, F. & Ridolfi, L., 2017. Multipurpose Design of the Flow-Control System of a Steep Water Main. *J. Water Resour. Plann. Manage., 144.2,* p. 05017018.

Fuller, W. A., 2009. *Measurement error models.* s.l.:John Wiley & Sons.

Gertler, J., 1988. Survey of model-based failure detection and isolation in complex plants. *IEEE Control systems magazine 8.6,* pp. 3-11.

Gertler, J., 2015. *Fault Detection and Diagnosis.* London: Springer.

Hwang, I., Kim, S., Kim, Y. & Seah, C., 2010. A survey of fault detection, isolation, and reconfiguration methods. *IEEE transactions on control systems technology 18.3,* pp. 636-653.

Isermann, R., 2005. Model-based fault-detection and diagnosis–status and applications. *Annual Reviews in control 29.1,* pp. 71-85.

Massarutto, A., 2000. Agriculture, water resources and water policies in Italy. *Fondazione Eni Enrico Mattei, Milano, Italy.*

Meseguer, J. & Quevedo, J., 2017. Real-time monitoring and control in water systems. *Real-time Monitoring and Operational Control of Drinking-Water Systems, Springer, Cham,* pp. 1-19.

Özyurt, D. B. & Pike, R. W., 2004. Theory and practice of simultaneous data reconciliation and gross error detection for chemical processes. *Computers & chemical engineering 28.3,* pp. 381-402.

Ragot, J. & Maquin, D., 2006. Fault measurement detection in an urban water supply network. *Journal of Process Control 16.9,* pp. 887-902.