Data analytics methodology for monitoring quality sensors and events in the Barcelona drinking water network
D. García, R. Creus, M. Minoves, X. Pardo, J. Quevedo and V. Puig

ABSTRACT
Water quality management is a key area to guarantee drinking water safety to users. This task is based on disinfection techniques, such as chlorination, applied to the drinking water network to prevent the growth of microorganisms present in the water. The continuous monitoring of water quality parameters is fundamental to assess the sanitary conditions of the drinking water and to detect unexpected events. The whole process is based on the assumption that the information retrieved from quality sensors is totally reliable, but due to the complexity of the calibration and maintenance of these chemical sensors, several factors affect the accuracy of the raw data collected. Consequently, any decision might be based on a non-solid base. Therefore, this work presents a data analytics monitoring methodology based on temporal and spatial models to discover if a sensor is detecting a real change in water quality parameters or is actually providing inconsistent information due to some malfunction. The methodology presented anticipated by 12.4 days, on average, the detection of a sensor problem before the fault was reported by the water utilities expert using knowledge accumulated with visual analysis. The proposed methodology has been satisfactorily tested on the Barcelona drinking water network.

Key words | Barcelona drinking water network, critical infrastructure, data-driven approach, fault detection, time series

INTRODUCTION
One of the main tasks of the water utilities (WU) is to transport and supply drinking water to users throughout water distribution systems (WDS). Two of the WU’s main areas of concern are, on the one hand, the operations department, to manage hydraulic infrastructure (e.g., pumping stations, reservoirs, pipes, etc.), and on the other hand, the water quality control department, to manage drinking water safety. Furthermore, different legal frameworks regulate the quality of drinking water supplied.

Water quality monitoring and control management programmes involve several tasks. As detailed in Bartram & Ballance (1996), such tasks are monitoring network design (e.g., which parameters have to be measured, how often, etc.), laboratory work (e.g., chemical analysis, laboratory tests, etc.) and analytical quality assurance (e.g., production of reliable data), among other elements.

There are several techniques to treat the water in WDS and keep it healthy for human consumption. One common disinfection technique is the chlorination of water. This process consists of injecting chlorine or derivatives in the water. The injected chlorine is consumed (i.e., by chemical reaction) in the WDS due to two main factors (Powell et al. 2000): on the one hand, due to reactions in the bulk water as, for example, by the presence of organic content in the water, by decay of the initial chlorine concentration because of the physical conditions (e.g., temperature); on
the other hand, the chlorine reacts at the pipe wall, known as biofilm (a group of microorganisms adhered to the pipes’ surface).

The chlorine in the water drops exponentially as follows:

\[ C(t) = C_0 \cdot e^{-kT} \]  

(1)

where \( C(t) \) is the chlorine concentration (mg/L) at the instant \( t \), \( C_0 \) is the initial chlorine concentration and \( T \) the time interval since the injection.

Thus, in order to keep residual chlorine in the water distribution network after a certain time \( T \), it is necessary to inject a certain chlorine dose \( C_0 \). The chlorine injection, usually done in the reservoirs, is regulated by an automatic controller, where a feedback control loop (typically based on a proportional-integral-derivative controller) (Figure 1), injects a quantity of chlorine \( u \) determined by the error \( e \) between the concentration reference \( r \) and the measured chlorine concentration \( y_m \).

The WU monitors the water quality parameters with online water quality sensors (multi-parametric and single-parametric) installed along the water transport and distribution networks. The most common water quality parameters monitored on-line are conductivity, temperature, pH and chlorine. Other interesting parameters, such as total organic carbon (TOC), are well-known indicators of water quality. Moreover, laboratory analyses of water samples taken from different points of the network are essential to analyse biological and chemical components unobserved by the on-line sensors, or even to contrast them against on-line observations.

Quality sensors require a specific calibration planning prescribed by the manufacturer depending on the sensor model to guarantee the reliability of the observations.

Moreover, a preventive maintenance planning (e.g., bimonthly or quarterly) is also specified by the manufacturer to preserve data reliability.

Even though applying preventive planning, these quality sensors could be affected by several problems, such as the ones listed in Table 1. Thus, a corrective planning is always required to solve these unexpected problems affecting the sensors’ reliability.

There has been significant research to detect and avoid intended and unintended injection of hazardous substances in WDSs to guarantee the drinking water safety. Several works have studied this particular subject in order to detect water contamination events. In Byer & Carlson (2005), different contaminants introduced into tap water were detected measuring pH, turbidity, conductivity, TOC and chlorine, and establishing as detection limits a threshold based on three times the standard deviation above the average of each magnitude. In Hou et al. (2014), a probabilistic principal component analysis method using UV-Vis spectrometers was detailed to detect contaminant injection into WDS. In Eliades et al. (2014), a model-based approach considering the chlorine input injection was used to compute bounds to compare with the sensors’ measurements. In Hall et al. (2007), a benchmark of a set of sensors from different manufacturers measuring distinct quality parameters was presented, allowing analysis and comparison of the sensitivity on the presence of various contaminants. In Hart et al. (2010), operational data and water quality were combined to reduce the false positive rate in the quality event detection. In Ba & McKenna (2015), different change-point detection algorithms were applied to the residuals of an autoregressive model. Sensor placement is also an important topic to improve quality monitoring, meanwhile reducing operational costs, as discussed in Rathi & Gupta (2014). The hydraulic model and a simulation software are proposed in Nejjari

Table 1 | Main factors affecting the information gathered from water quality sensors

<table>
<thead>
<tr>
<th>Cause</th>
<th>Consequence</th>
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<tbody>
<tr>
<td>Communication problem</td>
<td>Data gap</td>
</tr>
<tr>
<td>Loss of sensitivity</td>
<td>Flat signal or slow drift down</td>
</tr>
<tr>
<td>Electronic malfunction</td>
<td>Noise and peaks in the signal</td>
</tr>
<tr>
<td>Miscalibration of the sensor</td>
<td>Offsets affecting the real value</td>
</tr>
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</table>

Figure 1 | Chlorine injection process.
et al. (2012) to detect and localize water quality abnormal parameters in the WDS.

Model-based approaches, such as in Eliades et al. (2014) and Nejjar et al. (2012), have the main drawback that the performance depends directly on the water network model’s accuracy. Moreover, due to the complex behaviour of the water parameters, it is unfeasible to develop an accurate physical model to describe the water quality dynamics. Hence, data-driven approaches are very interesting in this case and therefore widely used.

In addition, a major drawback, in general, of the existing approaches to detect drinking water quality events is that they are based on the assumption that data gathered from these sensors are accurate and precise. However, as we have pointed out, raw data from quality sensors might not be ready for analysis or to draw solid conclusions. Unreliable water quality information is a serious problem for the WU in the quest to guarantee a water supply that assures the users’ health.

Hence, the main motivation of this work is to provide a data analytics methodology for monitoring quality sensors and events applicable to drinking water networks, such as those mentioned before.

The contributions of this work are two-fold. On the one hand, this work provides a methodology to get a solid information basis, discarding unreliable data, to improve the decision-making of the WU in water quality management. On the other hand, a set of indicators is provided that allow improvement of preventive planning, reducing the number of expensive corrective actions.

This work is focused on the application of the proposed methodology to solve the problem of quality events and unreliable sensors’ detection in a real WU with on-line monitored water quality parameters. In particular, the proposed methodology has been satisfactorily tested on the Barcelona drinking water network.

**CASE STUDY**

The case study, used to illustrate the proposed methodology for monitoring quality sensors and events, is based on the Barcelona drinking water network. The Barcelona drinking water network is a complex WDS of over 4,600 km that supplies drinking water to 218 demand sectors. In this WDS, thousands of sensors are installed throughout the network to know with precision the hydraulic state of the network in order to control and manage it efficiently. In addition, quality sensors and analysers are installed to handle the water quality control.

For illustrative purposes, this paper is focused on that part of the network depicted in Figure 2. The water supply for this zone can come from two different water sources: the rivers Ter and Llobregat. It has been carefully selected with the help of the network managers, as it presents typical issues affecting the entire network.

The tank collects water to satisfy the three demand sectors. A chlorination process is continuously undertaken in this tank based on an actuator (chlorine injection), a chlorine analyser and some reference given by the WU’s operators. At the entrance to each demand sector, a multi-parameter water quality sensor is installed to monitor and control the quality of the supplied water.

The WU collects hourly observations from multi-parameter sensors and 15-minute observations from chlorine analysers. The parameters observed are temperature, conductivity, pH and chlorine. The single-parameter sensors measure chlorine.

The water quality data collected are analysed by the experts using a visualization software to check for any existing quality event or sensor problem. Another software...
system allows the experts to contrast field samples analysed in the laboratory against the data collected from the sensors.

The methodology, presented next, has been inspired by the knowledge of the experts to analyse, check and even forecast problems in the water quality system.

**METHODOLOGY**

The methodology described in this section describes and analyses the procedure followed to obtain a robust decision regarding the two monitoring objectives. As we discussed before, the first objective is to detect changes in the water quality parameters that can compromise the safety of the water supplied, and the second objective is to discriminate whether the problem detected is a real change in the water quality parameters or whether it has been generated by unreliable observations due to some of the problems presented in Table 1.

**Data pipeline**

The methodology is based on a data pipeline of four steps, depicted in Figure 3. These steps are divided into two blocks by a dashed line: on-line and off-line. The training and validation stages are required to initialize and calibrate the models with historical data. Once the models are calibrated, the on-line stages are able to process, computationally efficiently, new incoming data streams. First, a pre-processing stage prepares and cleans the raw data: remove the noise, remove outliers, establish a regular sampling time and apply some transformations (differencing and standardizing). Then, a training stage builds the models of the methodology, detailed next, using a given training data set, in order to characterize the normal state of the system. Using these models, a validation stage is executed on an independent data set (validation data set) to quantify the fitness of the models to the real behaviour and to determine the thresholds of the models. Finally, the testing stage runs the models on a test data set. This data set, based on historical data, includes events. Hence, a performance evaluation to detect real sensor faults and quality events can be performed, as we will show in the ‘Results’ section.

Note that calibration and validation stages use independent data sets to avoid common problems when fitting a model (e.g., over-fitting).

As mentioned above, in the pre-processing stage, we first remove the outliers from the hourly observations $y(t)$ collected by the WU. We define an outlier as any observation more than three times interquartile ranges (IQRs) above the third quartile.

The next step standardizes the data with $Z$-score scaling of each quality parameter observed:

$$Z(t) = \frac{y(t) - \bar{y}}{\sigma} \quad (2)$$

The resulting signal has null mean and one as standard deviation. Then, a moving average with a sliding window of length $n$ is applied to filter the noise:

$$S(t) = \frac{Z(t) + Z(t-1) + \ldots + Z(t-n-1)}{n} \quad (3)$$

Finally, the differences between observations are computed (i.e., differencing) to make each time series stationary:

$$Y(t) = S(t) - S(t - 1) \quad (4)$$
In this work, we have considered two types of models to characterize the quality time series. On the one hand, time series models (TSM) capture the temporal redundancy. In particular, we consider in this work the Holt-Winters method (Winters 1960), the multivariate differences algorithm (MV) (McKenna et al. 2008) and an artificial neural network (ANN) trained with historical data to forecast observations (Palani et al. 2008). On the other hand, spatial models (SM) express the relations between sensors that are hydraulically related. For instance, a sensor located in the water distribution network should not observe an increase in the chlorine concentration if this event is not observed first by the sensor located in the tank. Note that this rule makes the assumption that the reference sensor (placed in the tank) is more reliable than the sensor placed in the distribution network. This is a fair assumption, given that the WU installs high-end chlorine analysers in tanks and more common quality sensors in the distribution network.

**TSM**

The TSM based on the Holt-Winters (Winters 1960) method for a time series with length \( L \) is:

\[
y(t + h) = a(t) + h \cdot b(t) + s(t - p + 1 + (h - 1)) \mod (L),
\]

where \( a(t) \), \( b(t) \) and \( s(t) \) are updated by:

\[
a(t) = a \cdot (y(t) - s(t - L)) + (1 - a) \cdot (a(t - 1) + b(t - 1))
\]

\[
b(t) = \beta \cdot (a(t) - a(t - 1)) + (1 - \beta) \cdot b(t - 1)
\]

\[
s(t) = \gamma \cdot (y(t) - a(t - 1) - b(t - 1)) + (1 - \gamma) \cdot s(t - L)
\]

where the parameters \( a, \beta \) and \( \gamma \) are obtained by minimizing the squared one-step prediction error using the training data.

Thus, a TS model \( \hat{Y}_p(t) \) is obtained per each water quality parameter \( p \) observed for each sensor \( s \). The following residual from the measured signal and the prediction allows changes to be detected:

\[
r_{TS}(t) = \hat{Y}(t) - Y(t)
\]

The multivariate distance algorithm (McKenna et al. 2008) allows changes to be detected in a group of parameters. In this work, the group of parameters are the ones measured by each multi-parameter device. The MV is expressed as:

\[
r_{MV}(t) = \sqrt{\frac{1}{n} \sum_{j=1}^{n} [Y_j(t) - \bar{Y}_j]^2} - \sqrt{\frac{1}{n} \sum_{j=1}^{n} [Y_j(t - 1) - \bar{Y}_j]^2}
\]

where \( \bar{Y}_j \) is the mean value of the parameter \( j \).

ANNs have been widely used in modelling time series in water networks, for example, water demands (Wu et al. 2014). In Palani et al. (2008), ANNs were used to learn existent linear and non-linear relationships between factors from water quality data in order to forecast these variables. In Sun (2013), ANN models were developed to predict groundwater level changes using a set of predictors: previous precipitation, terrestrial water storage change and maximum and minimum temperatures. In Valipour et al. (2015), the goal was to forecast the inflow to Dez Dam reservoir using ANN, auto regressive moving average (ARMA) and auto regressive integrated moving average (ARIMA) models. The authors identified that the ARMA and ARIMA models performed better to forecast the inflow for the next 12 months, and ANN models performed better to forecast the next 5 years. In Valipour (2016), three different structures of ANN, the non-linear autoregressive neural network (NARNN), the non-linear input–output and the NARNN with exogenous input, were compared to forecast the precipitation in Gilan to detect drought and wet year alarms.

The ANN is a set of units (neurons) connected to each other. These units are organized in three layers. The input layer comprises units that receive the inputs from the outside, the output layer units generate the outputs to the outside and the hidden layer(s) has hidden units that link the input layer and the output layer via weighted connections. Here, we train an ANN to forecast chlorine at time \( t \), as a regression model. Thus, the output layer is composed of only one node. The inputs of the ANN are the previous chlorine observations \( \hat{y}(t) = f(y(t - 1), y(t - 2), \ldots, y(t - N)) \). Then, the residual is expressed as follows

\[
r_{ANN}(t) = \hat{y}(t) - y(t)
\]
Figure 4 shows the resulting ANN with the 12 inputs (I1, I2, ..., I12), the hidden layer with three hidden units (H1, H2 and H3), the output layer with one unit (O1), and B1 and B2 are bias layers that apply constant values to the nodes, similar to intercept terms in a regression model. The black lines are positive weights and the grey lines are negative weights.

The number of input units and hidden units have been obtained by evaluating different sets of parameters and selecting the model with minimal root-mean-square error (RMSE), defined as follows:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left( y(t) - \hat{y}(t) \right)^2}
\] (10)

SM

Two spatial relations are considered in this methodology: the predecessor rule (PD) and the divergence measure (DV).

As mentioned before, it is not possible to observe an increase in the chlorine concentration at the sensor \( Y_s(t) \), placed in a demand sector, if this event is not observed first by the sensor \( Y_r(t) \), located in the tank. This simple statement is expressed in the following relation using the standardization process (Equation (2)):

\[
Z_s(t) \leq Z_r(t)
\] (11)

Hence, the residual of the PD can be formulated as follows:

\[
r_{PD}(t) = (Z_r(t) - Z_s(t))^2
\] (12)

This residual is first evaluated in normal conditions (without faults) to establish a threshold. Hence, we can compare the residual computed on-line against the threshold to detect a divergence between a reference sensor \( r \) and a spatially linked sensor \( s \).

Furthermore, there are hydraulic configurations presenting various spatially related sensors. In this situation, the observations collected of the same magnitude from different sensors should converge. Thus, we can generalize (Equation (12)) to measure the convergence between various hydraulically linked sensors:

\[
r_{DV}(t) = \sum_{j=1}^{N} (Z_s(t) - Z_j(t))^2, j \neq s
\] (13)

It must be noted that the conclusions obtained from this model will be wrong or meaningless if two or more sensors are observing inaccurate data at the same time. For this reason, this model is discarded from the methodology.

Fault diagnosis

Using any of the proposed models alone, it will only be possible to detect that something unexpected, based on the historical knowledge, has occurred. However, it will not be possible to distinguish whether the problem is a sensor fault or a quality event.

In particular, the Holt–Winters TSM, MV and ANN models are able to detect unexpected changes in the quality
parameters signal, but they do not allow determination of whether the change produced is a real change in the water quality parameters or, if it is actually due to inaccurate data collected from a sensor affected by some problem. Hence, spatial information is required to contrast the events detected against additional information provided by other related sensors.

Thus, the SM, DV and PD are considered to provide this additional information.

Furthermore, some of the temporal models presented in the previous section are redundant regarding our goals. For instance, the MV, Holt–Winters and ANN detect abrupt changes in the behaviour of the quality measurement signal. A comparison among them will be presented in order to select the one that presents the better detection performance. Analogously, the spatial-based models, PD and DV, track the dissimilarity with respect to other spatial related sensors. Again, after comparing them, the one that provides the best detection performance is selected.

Combining all this knowledge, a fault diagnosis scheme is developed to interpret the combination of the results and provide the key indicators to the WU to improve and anticipate the sensors’ maintenance operations.

Each model-based residual is binarized in the detection test, i.e., the test generates a 1 if the residual is within the model threshold and 0 otherwise. The lower bound $\theta_{LB}$ and upper bound $\theta_{UB}$ for (Equation (7)) and (Equation (9)) are estimated based on the following expression:

\begin{align}
\theta_{LB} &= Q_1 - 3 \cdot IQR_x \\
\theta_{UB} &= Q_3 + 3 \cdot IQR_x
\end{align}  \tag{14}

where $Q_1$ and $Q_3$ are the first and third quartiles, respectively, and $IQR_x$ is the interquartile range (the difference between the third and first quartiles) obtained from the residuals of the validation data set.

The upper bound of (Equation (12)) (note that the residuals are squared) is:

\begin{equation}
\theta_{UB} = C \cdot \max(r_x)
\end{equation}  \tag{15}

where $C$ is the constant that defines the sensitivity of the model and $r_x \in \{TDV, TPD\}$ using the validation data set.

The fault diagnosis system can be formalized as a discrete-event system. Figure 5 presents the state diagram. From the normal state there are two possible outcomes: a quality event or a sensor fault. When a sensor fault is detected, a maintenance operation is performed. A quality event can be caused by an intended action (e.g., hydraulic action, chlorine reference change) or by some unexpected infiltration.

The states are characterized in Table 2 as a function of the activation of model-based tests, except the calibration state, which is clearly known by the WU maintenance department.

As detailed in Table 2, a sensor is in normal state when all the tests are not active. A quality event is diagnosed when the PD test is not active and ANN is active. When the PD test is activated, a sensor fault is diagnosed, regardless of the ANN test.

### RESULTS

In this section, results based on the Barcelona case study, previously detailed, are presented to show the performance of the methodology proposed in this work.

The data used to generate the results come from the multi-parametric (chlorine, pH, temperature and...
conductivity) sensors (0794, 0795 and 0801), the chlorine analyser X127701D and the events reported by the WU experts to the maintenance department (detailed in Figure 2).

The historical data of events allow us to analyse the performance of our diagnosis approach. The performance measure selected is the anticipation in days and the false alarms’ rate.

A 1-year data set has been divided into three independent subsets: a training set (1 month of data) is used to calibrate the models, a validation set (15 days) is used to analyse how the model generalizes with new data, and finally, a test set (7 months) is used to show the performance of each model detailed in the methodology. We assume that the training and validation sets have no events in order to characterize the system in a normal state (i.e., without faults).

A first scenario considering two chlorine measurement signals is shown in Figure 6. The solid black line corresponds to the chlorine sensor 0794 placed at a demand sector and the dotted black line is the analyser X127701D placed at the reservoir where the chlorination process is done. The broad vertical lines indicate the time instants of the events reported by the WU experts, based on their accumulated knowledge. There are five events reported in a 1-year period of data. The first, third, fourth and fifth events show the most common problem with an online chlorine sensor: the sensitivity loss. This is caused by the degradation of the membrane and the electrolyte of the chlorine sensor. If we look closely, the patterns of the chlorine signals are fairly similar just before the events were reported: in a certain time instant, the chlorine signal decays while the transport sensor does not indicate any decay. The WU experts detect this event and report the event to the maintenance department to plan the corrective actions.

Figure 7(a) shows the first 2 months of raw data collected from the water demand sector presented in Figure 2 – the three multi-parametric sensors of the distribution network with ids: 0794, 0795 and 0801; and the transport analyser with the id X127701D. Figure 7(b) shows the preprocessed data, i.e., without outliers, smoothed and standardized using the Z-score (see the section ‘Data pipeline’ for further details). The plots, stacked vertically, are the set of parameters observed and are, from top to bottom: conductivity (C) in μS/cm, chlorine (Cl) in mg/L, pH and temperature (T) in °C, respectively. This scenario corresponds to the first fault reported in Figure 6, i.e., the first broad vertical line. As it can be seen, the chlorine signal of the sensor 0794 shows a slight drift during 20 days regarding

![Figure 6](image_url)
Figure 7 | Stacked plots (by quality parameter) from the three multi-parameter quality sensors and the chlorine analyser.
the rest of the chlorine sensors 0795, 0801 and X127701D. Moreover, note that there is a clear distance between its pH signal against 0795 and 0801 pH signals.

This particular scenario was detected and fixed by the WU as follows. On 21 January 2014, the quality water data analyst, in a check routine, detected a slow chlorine

![Figure 8](http://iwaponline.com/jh/article-pdf/19/1/123/734070/jh0190123.pdf)

**Figure 8** | Models’ residuals of the first chlorine event of sensor 0794.
decay of the 0794 sensor compared against the other two sensors (0795 and 0801) and to the transport sensor (X127701D). Once the problem was discovered, the water quality analyst reported the event to the maintenance department. Then, on 22 January, a maintenance technician made a readjustment in order to recalibrate the sensor. Due to this operation, the 0794 sensor showed an abrupt increase in chlorine and a decrease in pH at the same time, during 2 days (22 to 24 January), and after this period it converges again.

Figure 8(a) shows the residuals of the models (detailed in the methodology). Figure 8(b) shows the binarized residuals (a binarized residual is 1 if exceeds the model’s threshold and 0 otherwise, see the section ‘Fault diagnosis’ for further details) to visualize clearly when a residual exceeds the detection threshold. The ANN (top plot) detects the maintenance calibration operation (from 22 to 24 January). However, looking at the ANN binarized residual, it can be seen that it starts to detect something a day before the operation. The same happens with the DV model, but it starts to detect something on 12 January. Moreover, the HW and MV only detect the maintenance operation. These models, as mentioned before, are not capable of detecting a slow degradation fault, as in this case.

The PD model has detected a divergence between the sensor 0794 and the transport analyser X127701D since 15 January. As it can be seen in Figure 8(b), there is a sequence of two solid blocks: the first detection, from 15 to 21 January, of the degradation fault, and the second from 22 to 24 January is the maintenance operation.

The models DV and PD perform in a similar way, detecting divergence between spatial related sensors and able to detect a drift fault. The models HW and ANN detect abrupt changes but not a drift fault. The MV model is the least sensitive model at detecting extreme events, the peaks being caused by the maintenance operation.

Figure 9 shows another scenario. This is a real quality event where the chlorine concentration increased from 0.7 to 0.9. The resulting binarized residuals are shown in Figure 10. As it can be seen, the PD model does not detect any event, but the other models detect the change in the pattern of the signals caused by the new chlorine injection configuration.

Figures 11–13 show the fault diagnosis of the chlorine sensors 0794, 0795 and 0801, respectively. Tables 3–5 show the diagnosis anticipation of our approach regarding the events reported by the WU experts. Each row represents a sensor fault detection produced by our approach. The columns start
Figure 10 | Binarized residuals of the models during a chlorine set point change.

Figure 11 | Chlorine signals from 0794 sensor and X127701D and fault diagnosis.
Figure 12  Chlorine signals from 0795 sensor and X127701D and fault diagnosis.

Figure 13  Chlorine signals from 0801 sensor and X127701D and fault diagnosis.
detection and end detection are the date interval during which our approach detects a sensor fault, the column event reported is the date when the WU expert detected the fault and anticipation is the number of days in advance provided by our approach regarding the event reported.

The rows with a blank in the event reported column, apparently false alarms, are motivated by two causes. On the one hand, the table shows only reported events, not planned maintenance operations (information not available). Thus, some events detected by our approach have been fixed in the maintenance operations before being detected and reported by the WU experts. For instance, Figure 13 shows a decay of the 0801 chlorine signal starting at the end of July until the end of August. At the end of August, an abrupt rise of chlorine is caused by a planned maintenance operation. On the other hand, false alarms occur due to the tight thresholds considered. For instance, the 0801 sensor fault detected on 2014-05-09 is for 1 day only (it does not appear in the bottom colour bar of Figure 13 because of the short width).

With the approach presented in this work, we anticipated by 12.4 days, on average, the detection of a sensor problem before the fault was reported by the WU expert using knowledge accumulated by visual analysis.

**CONCLUSIONS**

This paper has proposed a methodology to detect water quality changes based on multi-parametric sensors. It has been shown that it is not possible, looking at the different tests separately, to distinguish between a sensor fault and an actual quality event. A fault diagnosis algorithm has been developed that is able to distinguish between water quality events and problems affecting the sensors, such as loss of sensitivity.

This approach has been applied to the Barcelona water network, and the results obtained show that the methodology detailed is able to anticipate the detection of future problems in chlorine sensors compared to the visual analysis applied by WU experts. Hence, the proposed approach improves the water quality control management and reduces the corrective maintenance actions. As a future research, it is planned to integrate the hydraulic model in the methodology in order to reduce the uncertainty of the methodology, and extend the proposed methodology to predict the degradation of the sensors and to plan the maintenance according to the sensors’ health.

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Fault detection, diagnosis and anticipation of sensor 0794</th>
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<tbody>
<tr>
<td>Start detection</td>
<td>End detection</td>
</tr>
<tr>
<td>5</td>
<td>2014-07-13</td>
</tr>
<tr>
<td>6</td>
<td>2014-08-22</td>
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<table>
<thead>
<tr>
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<td>End detection</td>
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<tr>
<td>1</td>
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</tr>
<tr>
<td>5</td>
<td>2014-07-18</td>
</tr>
<tr>
<td>6</td>
<td>2014-08-27</td>
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<td>7</td>
<td>2014-09-12</td>
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<th>Fault detection, diagnosis and anticipation of sensor 0801</th>
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<tr>
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<td>End detection</td>
</tr>
<tr>
<td>5</td>
<td>2014-07-13</td>
</tr>
<tr>
<td>6</td>
<td>2014-08-22</td>
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