Heuristic burst detection method using flow and pressure measurements

M. Bakker, J. H. G. Vreeburg, M. Van De Roer and L. C. Rietveld

ABSTRACT

Pipe bursts in a drinking water distribution system lead to water losses, interruption of supply, and damage to streets and houses due to the uncontrolled water flow. To minimize the negative consequences of pipe bursts, an early detection is necessary. This paper describes a heuristic burst detection method, which continuously compares measured and expected values of water demands and pressures. The expected values of the water demand are generated by an adaptive water demand forecasting model, and the expected values of the pressures are generated by a dynamic pressure drop – demand relation estimator. The method was tested off-line on a historic dataset of 5 years of water flow and pressure data in three supply areas (with 650, 11,180 and 130,920 connections) in the western part of the Netherlands. In the period 274 bursts were reported of which, based on the definition we propose in this paper, 38 were considered as relatively larger bursts. The method was able to detect 50, 25.9 and 7.8% in the considered areas related to all bursts, and around 80% in all three areas related to the subset of relatively larger bursts. The method generated false alarms on 3% of the evaluated days on average.

Key words | burst detection, data-driven pressure model, demand forecasting, water distribution networks

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INTRODUCTION

Pipe bursts in Dutch drinking water distribution systems

Response to pipe bursts and leakages are part of the daily operation of water companies. The burst frequency on water mains in the Netherlands is 7 bursts/100 km/year (Trietsch & Vreeburg 2005; Vreeburg *et al.* 2013). This number is low compared to other countries: e.g., United States, 17 bursts/100 km/year (AWWA 2007; Srirangarajan *et al.* 2013); the city of Trondheim, Norway, 30 bursts/100 km/year (Røstum 2000); three Canadian water companies, 34 bursts/100 km/year (Pelletier *et al.* 2003). The IWA base level of burst frequencies for well-maintained systems is 13 bursts/100 km/year (Lambert & Thornton 2011). A possible explanation for the low burst rate in the Netherlands is the relatively low pressure in the networks because the country is rather flat and densely populated. Based on observations of 112 systems in ten different countries, Thornton & Lambert (2006) showed that the burst frequency is reduced by 51% when reducing the maximum pressures by 37%. Other indicators showing a good performance of the Dutch distribution networks are the low rate of physical losses of 5% on average (Beuken *et al.* 2007) and a low infrastructure leakage index of 0.7 (Lambert *et al.* 1999). The ground conditions in the country favour leaks showing rapidly at the surface (Lambert *et al.* 1999) which results in a quick detection and repair of bursts.

As a result, the issue of pipe bursts is not a top priority for the water companies, and budgets are limited to minimize the number and the impacts of bursts. Still, a few larger bursts occur occasionally which have disruptive consequences for the environment and people. In order to improve the service level to consumers and to act proactively in case of a pipe failure, the Dutch water companies wish to detect and locate bursts at an early stage.

Unmanned operation of water systems

Water companies are gradually transforming their operations from local and manual operation to centralized unmanned operation (Worm *et al.* 2010). Operators who are continuously controlling a single location are replaced by supervisors who are supervising a number of locations in a region only during office hours. This increasing distance between the human operator and the water production and distribution processes results in an increasing risk that failures in the system remain unnoticed. Distribution networks are often only monitored by a simple 'flat-line' alerting system that raises an alarm when flow or pressure exceeds a static threshold value. Mounce *et al.* (2010) showed the limitations of such a system in detecting pipe bursts, and as a result many bursts stay unnoticed. Often, the water companies only take action after consumers complain of low pressure or consumers reporting flooding caused by a burst pipe.

Life cycle of pipe bursts

Thornton *et al.* (2008) classified leakages in water distribution networks into 'background' (small continuous running leakages), 'unreported' (slightly bigger leakages, that tend to increase and need attention) and 'reported' (big leaks that need to be repaired as soon as possible). After the beginning of a burst, some time elapses before it is reported and the water company is aware of the situation. In the time frame between the beginning and the isolation of the burst, the broken pipe causes negative consequences like interruption of supply, water loss, and damage to streets and houses. The aim of a burst detection method is to minimize the time frame between the beginning and the moment that the water company is aware of the burst. This is the unawareness period in the life cycle of a burst, as shown in Figure 1 (based on WRc (1994), and expanded by Bakker *et al.* (2012)). The other periods, the awareness period, the location period, the isolation period and the repair period, are not affected by a burst detection method. This indicates that such a method will only be valuable for bursts that have a relatively long unawareness period. Typically, this is the case for smaller bursts where only a small amount or no water surfaces, or for larger bursts that occur at night and surfacing water remains unnoticed.

Previous work

Pipe burst detection can be considered as the application of anomaly detection techniques to a specific, narrow defined phenomenon. Anomaly detection is defined as 'the problem of finding patterns in data that do not conform to expected behaviour' (Chandola *et al.* 2009). Anomaly detection can be divided in two sub-problems: (1) generating 'expected behaviour' of the phenomenon; and (2) evaluating the 'non-conformity' of observed and expected behaviour. For the detection of pipe bursts, various techniques can be used (Puust *et al.* 2010).

Monitoring hydraulic parameters (flow, pressure)

Flow and pressure are commonly measured in water distribution networks, and therefore used in most burst detection methods. The sampling interval of flow and
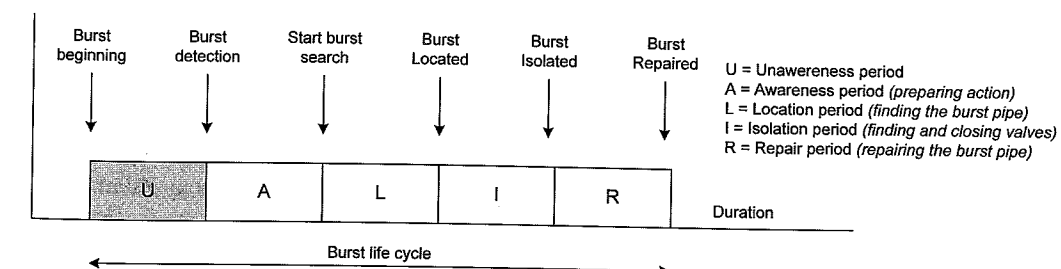

Figure 1 | Life cycle of a burst.

pressure sensors installed in the network is usually 15 min (Romano *et al.* 2013), but for burst detection both longer intervals (1 hour, e.g., Palau *et al.* (2011)) and shorter intervals are applied (5 min, e.g., Eliades & Polycarpou (2012); 1 min, e.g., Misiunas *et al.* (2006)). Mounce *et al.* (2012) studied the relation between the sampling interval and the performance of detection methods. The paper shows that shorter sampling intervals result in earlier detection, but questions if the earlier detection compensates the extra costs for communication and data handling.

Different techniques are used to generate 'expected' values of the flows and pressures, like artificial neural networks (ANN) (Mounce *et al.* 2002; Romano *et al.* 2012), support vector machines (Mounce *et al.* 2011), Fourier transformations (Eliades & Polycarpou 2012) and Kalman filtering (Ye & Fenner 2011). But the 'expected' value can also be defined as the mean of observations in a previous period, differentiated in week days and weekend days. When applying this approach, different models need to be constructed for each season or periodicity, because of the (seasonal) variation in the water demand. This simplified approach is especially used in combination with statistical approach, like cumulative sum method (Jung detection methods, like cumulative sum method (Jung *et al.* 2013) or principal component analysis (Palau *et al.* 2011). As the evaluation of (non-)conformity is based on a comparison of observed and expected values, the accuracy of the expected value under normal conditions plays a key role in the performance of the detection method. Surprisingly, in the above-mentioned papers, little attention is paid to the analysis of the performance of the applied models that generate the expected values.

For the detection of events, the deviation between expected and observed behaviour is evaluated. Different techniques are applied for this evaluation, like an ANN combined with a rule-based system (Mounce *et al.* 2003), fuzzy logic (Mounce *et al.* 2010), Bayesian inference systems (BISs) (Romano *et al.* 2013), a self-organizing map (Aksela *et al.* 2009) or CUSUM method (Misiunas *et al.* 2006; Jung *et al.* 2013).

Monitoring pressure transients

Pressure transients, which occur after a sudden failure (rupture) of a pipe, can be monitored to detect pipe bursts.

Transient monitoring consists of measuring pressure at different locations at high sampling rates (250 Hz (Srirangarajan *et al.* 2013) up to 2,000 Hz (Misiunas *et al.* 2005a)). By analysing these measurements, a pipe burst can be detected and the burst location can be approximated. Colombo *et al.* (2009) presented a literature overview of transient monitoring techniques. Brunone & Ferrante (2001) and Gong *et al.* (2013) studied transients in a single water pipe. Misiunas *et al.* (2005b) and Srirangarajan *et al.* (2013) studied transients in distribution networks, and Allen *et al.* (2012) tested this approach on a test bed in Singapore.

Although the above-mentioned papers report promising results, monitoring pressure transients to identify pipe bursts has some important disadvantages. The method is expensive because of the high sampling rates, which cannot be obtained with existing sensors and communication equipment. Furthermore, a large number of sensors need to be installed because pressure transients will only travel a few hundred metres (Srirangarajan *et al.* 2013). A second disadvantage is that transients will only arise, and thus can only be observed, at pipe failures that happen (almost) instantaneously. Pipe failures that develop more gradually will not induce a pressure transient, and will therefore not be detected by this technique.

Monitoring other parameters

Other parameters besides flow and pressure can be monitored to identify pipe bursts. Khan *et al.* (2005) applied opacity and temperature sensors for burst detection, and Mounce *et al.* (2002) applied opacity sensors in combination with flow and pressure sensors. Also multi-probe devices were applied, that measure, in addition to the hydraulic parameters, conductivity, pH, oxidation reduction potential and acoustics (Allen *et al.* 2012).

Performance evaluation

To develop and test detection methods, researchers have used different approaches. Some researchers only described the theoretical platform (Poulakis *et al.* 2003; Palau *et al.* 2011) or used simulated data (Misiunas *et al.* 2006). In most papers, the methods were tested on data from a real network. In some papers, this was done with data of a rather short period of several weeks to one month (Mounce *et al.* 2002), sometimes including engineered burst events (Mounce *et al.* 2003; Mounce & Machell 2006; Ye & Fenner 2011; Romano *et al.* 2013). In some other papers, the performance of the detection methods was evaluated over longer periods: 2–3 months (Mounce *et al.* 2010; Palau *et al.* 2011); 6 months (Aksela *et al.* 2009; Mounce *et al.* 2011); 12 months (Mounce & Boxall 2010; Eliades & Polycarpou 2012; Romano *et al.* 2012). Most papers present results obtained in off-line simulation; only the results presented in Mounce & Boxall (2010) and Mounce *et al.* (2010) were obtained by an implemented on-line system.

Development of heuristic burst detection method

In this paper, we describe a low-cost heuristic burst detection method that monitors existing flow and pressure measurements. The method uses only existing flow and pressure measurements, and no additional investments are needed for installing and operating new sensors. The key elements of the detection method are an adaptive water demand forecasting model and a data-driven pressure estimation model, that generate expected values of flow and pressure.

In the Materials and methods section, we describe the area and data we used to test the method, and we describe the method itself. In the Results section, we present the accuracy of the forecasting models, and the performance of the detection method expressed in detection probability (DP), rate of false (RF) alarms and detection time (DT). In the Discussion section, we discuss the results, and the final section presents the conclusions of this paper.

MATERIALS AND METHODS

Study area and dataset

To develop and test the burst detection method, we collected a dataset with historic flow and pressure measurements. We collected all measured flows and pressures of three supply areas (Rhine area, Wassenaar area and Noordwijk area) of the water company Dunea in the western part of the Netherlands. Data were available at 5 min intervals for the period 2007–2012 (630,296 values per time series). The flows and pressures were measured at the permanent assets of the water company (treatments plant, reservoirs, boosters and permanent measuring points) and were stored in a central database system. For the last 5 years (2008–2012), main repair records were available containing records of repairs carried out in the three areas. In these reported events, we distinguished between the total number of bursts and the number of relatively larger bursts. We subjectively defined relatively larger bursts as those where the burst flow exceeded the standard deviation of the demand forecast error. The three researched areas are shown in Figure 2 and the characteristics and reported incidents are summed in Table 1.

The largest area (Rhine area) contains 130,920 connections. This is a large area compared to district metered areas (DMAs) in other countries, which generally contain 1,000–3,000 properties (Thornton *et al.* 2008). The water supplied in this area is mainly produced at the Katwijk water treatment plant (1), and buffered in the clear water reservoirs Cronestein (2), Noordwijkerhout (3) and De Engel (5). These are ground level reservoirs that are filled during low demand (at night) with water from the network, and water is pumped water back to the network during high demand. The middle sized area (Wassenaar area) receives water from adjacent areas through four measured connections (measuring points 9 to 12). The small sized area (Noordwijk area) receives water from the Rhine area through the Nieuwe Zeeweg booster (6).

Heuristic burst detection method

We developed a heuristic burst detection method that is designed for on-line application to raise alarms in real time. In the case study presented in this paper, we applied the method off-line on the historic data from the Study area and dataset section. The method consists of four main steps: (1) generating expected values of water demands and pressures; (2) validity check of the signals and forecasts; (3) transformation of the measured and expected values; (4) analysis of the deviations between the measured and expected values, for A: generating threshold values based on historic data, and B: generating alarms by comparing the actual deviations with the threshold values. The detection method ran in parallel for all three monitored areas,
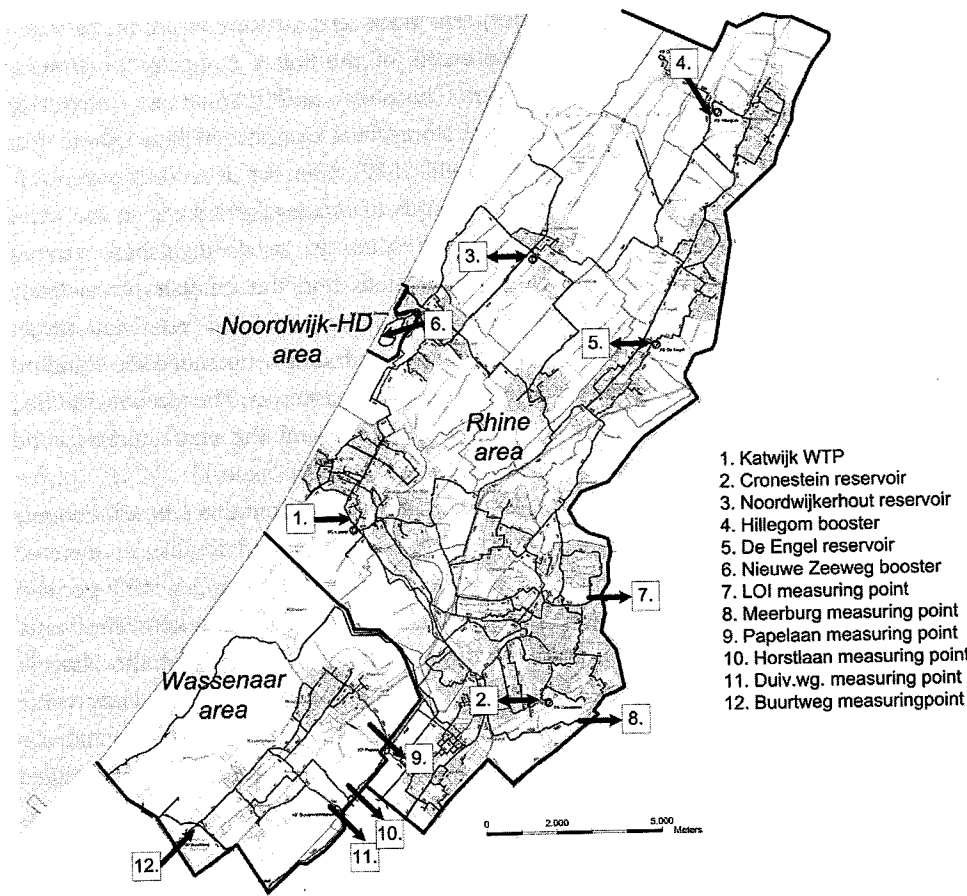
Figure 2 | Areas of the case study including the treatment plant, reservoirs, boosters and all measuring points.

1. Katwijk WTP
2. Cronestein reservoir
3. Noordwijkerhout reservoir
4. Hillegom booster
5. De Engel reservoir
6. Nieuwe Zeeweg booster
7. LOI measuring point
8. Meerburg measuring point
9. Papelaan measuring point
10. Horstlaan measuring point
11. Duiv.wg. measuring point
12. Buurtweg measuringpoint

Table 1 | Characteristics of the three researched areas (2008–2012)

Area	# Connections	Average demand [m³/h]	# Bursts [total/rel. larger]
1. Rhine area	130,920	2,290	242/24
2. Wassenaar area	11,180	212	26/10
3. Noordwijk area	650	31	6/4

where the results from one area were used when monitoring the other areas. The setup of the method is shown in Figure 3.

Generate expected values for demand and pressure

For each monitored area, the net water demand was determined by performing a water balance calculation. The net water demand in the area was the input for the (data-driven) adaptive water demand forecasting model described by Bakker et al. (2013b). This model generates a water demand forecast for the next 48 h with 15 min time steps. The model adaptively learns the normal demand patterns and factors for the 7 days of the week, and for a configurable number of deviant day types (like national holidays and primary school holiday periods). This forecasting model has been implemented in real time at a number of water supply systems for optimal control (Bakker et al. 2013a). For detection of pipe bursts, only the actual forecasted value (the so-called now-cast) was used. This now-cast was calculated by interpolating between the previous and the next 15 min time step forecast.

In the Rhine area, pressure was measured at the entry point and at eight other locations. We generated expected values for these pressures by deriving a relation
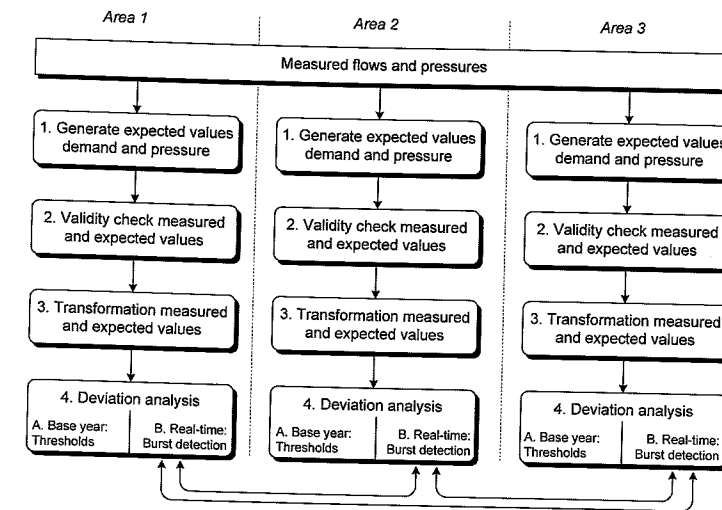
Figure 3 | Setup of the heuristic burst detection method.

between the pressure at the entry point and the pressure at a location. The intake flow or pump flow at a location plays an important role when calculating the expected pressure at that location. Therefore different relations needed to be made for situations with intake flows (Equation (1)), situation with (approximately) no flows (Equation (2)) and situations with pump flows (Equation (3)). We formulated the relations between the pressure at one location (p_{loc}) and the pressure at the entry point (p_{entry}) as:

$$Q_{loc} < -Q_{loc,min} \rightarrow P_{loc}$$
$$= P_{entry} + C_{1,1} + C_{1,2}.Q_{area}^2 + C_{1,3}.Q_{entry}^2 + C_{1,4}.Q_{loc}^2 \quad [kPa] \quad (1)$$

$$-Q_{loc,min} \leq Q_{loc} \leq Q_{loc,min}$$
$$\rightarrow P_{loc} = P_{entry} + C_{2,1} + C_{2,2}.Q_{area}^2 + C_{2,3}.Q_{entry}^2 \quad [kPa] \quad (2)$$

$$Q_{loc} > Q_{loc,min} \rightarrow P_{loc}$$
$$= P_{entry} + C_{3,1} + C_{3,2}.Q_{area}^2 + C_{3,3}.Q_{entry}^2 + C_{3,4}.Q_{loc}^2 \quad [kPa] \quad (3)$$

where Q_{area} is the net water demand in area, Q_{entry} is the water flow at the entry point, Q_{loc} is the water flow at the location, and $Q_{loc,min}$ is the threshold value to distinguish between zero flows, Equation (2), and non-zero flows, Equations (1) and (3). The three sets of parameters $C_{n,1}$ to $C_{n,4}$ were derived from the previous 4 days of data using the least squares method. Figure 4 shows an example of trends of measured and expected water demand and pressure.
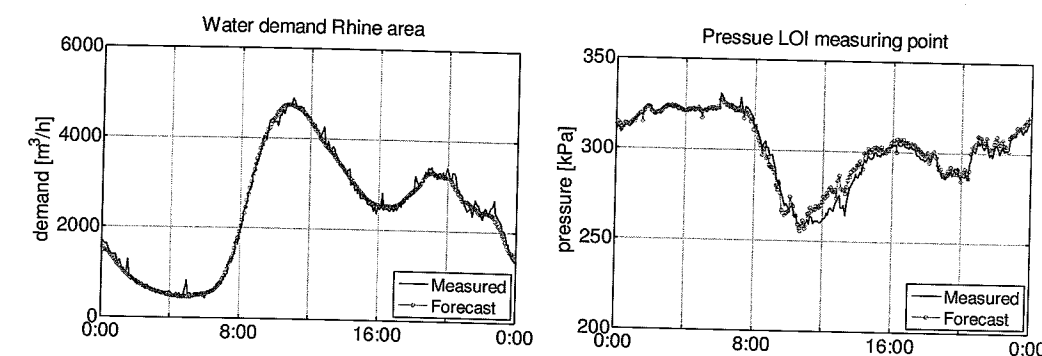

Figure 4 | Examples of trends of measured and expected values, with the water demand in the Rhine area (left graph) and the pressure at LOI measuring point (right graph).

Validity check measured and expected values

The measured signals can be invalid due to sensor failures and communication failures. To prevent false alarms caused by these failures, the validity of the signals were checked. A signal was considered invalid if: (1) the sensors' validity bit indicated a sensor or communication failure; (2) the value was outside a static upper/lower band that was configured for each signal individually (e.g., if a pressure measurement was <10 kPa or >500 kPa); (3) the value was exactly 0 (only for pressure measurements); (4) the signal was 'dead' (constant value). In addition to the validity check of the signals, the validity of the forecasts were checked as well. A forecast was considered invalid if the average forecast error of the previous 4 h exceeded a configurable threshold value. The invalid status of the forecast was reset if the invalid condition was not true for 24 h. When a signal or forecast was considered invalid, alarms were suppressed of the monitoring module that used the signal or forecast.

Transformation of measured and expected values

The measured time series of water demand and pressure showed unexplained variations due to random temporal and spatial variation in the water demand. These variations in the signal can be reduced by transforming the signal to a moving average, where the variations decrease as the time frame is increased. Reducing the unexplained variation enables closer monitoring without increasing the number of false alarms. However, when calculating the moving average, the deviant 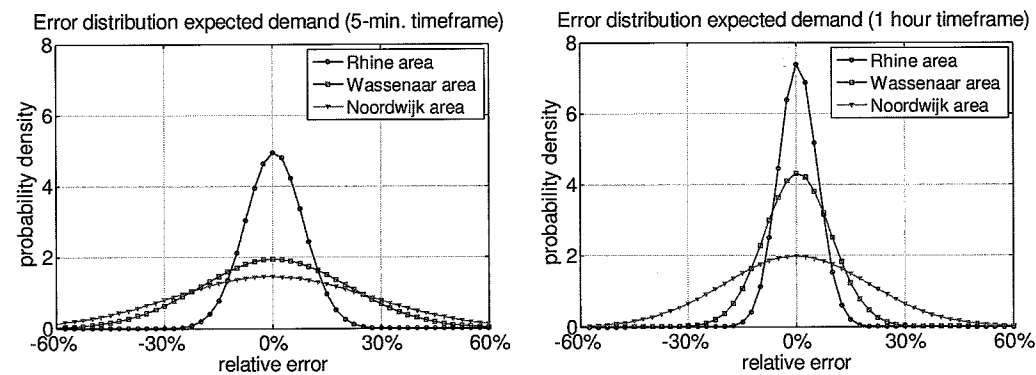values after the burst will be levelled off by normal values prior to the burst. This means that by taking the moving averaged value, smaller bursts can be detected but only some time after the beginning of the burst. In the burst detection method, the moving averaged signals over time frames of 5, 10, 15, 30, 60, 120 and 240 min were monitored. Figure 5 shows that the errors of the expected water demand were more centred around zero when the time frame was increased from 5 to 60 min.

Deviation analysis: off-line setting threshold values

Deviations between measured and expected values indicate a pipe burst. For monitoring purposes, threshold values need to be set to distinguish between normal forecasting inaccuracies on the one hand and possible burst events on the other hand. To determine the threshold values, we analysed the deviations in the year prior to the monitoring years. We performed two observations: 1. the deviations were not normally distributed around the average deviation, but the relative larger underestimates and overestimates had a higher probability; and 2. the relative (percentage) deviation of the water demands decreased as the forecasted value increased. Based on these observations, we chose to relate the monitoring threshold value to the 5% exceedance probability of the deviation. In addition, the expected values of the water demand were divided in five classes (from low to high demand) for which different 5% exceedance probability values were derived. Figure 6 shows an example of the analysis of the demand deviations, and the resulting 5% exceedance probability values that were used to set the monitoring threshold values.
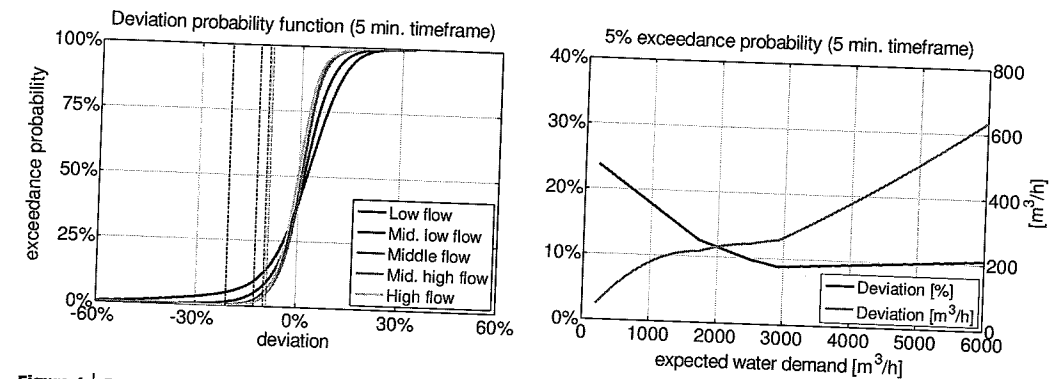

Figure 5 | Error distribution of the expected water demand in the three areas (left: 5 min time frame; right: 60 min time frame).

Figure 6 | Example of the deviation analysis of the 5 min time frame water demand forecast (Rhine area). The left graph shows the deviation probability functions of the five classes of expected water demand; the right graph shows the 5% exceedance probability function.

Deviation analysis: real-time burst detection

When applied in real time, the method raised an alarm when the deviation of any of the signals exceeded its threshold value. The threshold value was defined as the 5% exceedance probability value multiplied by C_{lim}. The C_{lim} value controls the performance of the method: a low value results in precise monitoring and many false alarms (high DP, high RF); a high value results in less precise monitoring and fewer false alarms (lower DP, lower RF). We evaluated the performance of the method with a default C_{lim} value of 2.5. This value was set (based on the analysis of the data in the year prior to the monitoring years) to limit the number of false alarms to approximately one per month per area (RF approximately 3%). In the Discussion section of this paper, we present a sensitivity analysis of the C_{lim} factor. Figure 7 shows an example of the method, where both the forecasted water demand (and related threshold values), and the actual measured demand are shown.
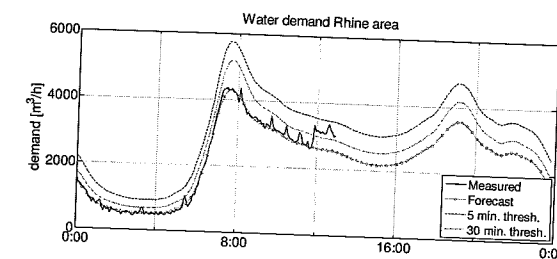
Suppressing alarms

Certain exceptional water demands are not forecasted properly by the forecasting model. The exceptional water demands occur often in all areas at the same time, because they are evoked by collective human behaviour. An example of this are the sudden peaks and drops in the water demand during and after important sports games (Bakker *et al.* 2003). This non-forecasted demand pattern may result in deviations that exceed the threshold value, resulting in false alarms. To eliminate those kinds of false alarms, the heuristic burst detection method simultaneously monitored the demand deviations in all areas. An alarm was suppressed in one area if the deviation in a neighbouring area exceeded its 5% exceedance probability value multiplied by C_{supp}. The default value of C_{supp} was 1.0, based on the analysis of the data in the year prior to the monitoring years. This alarm suppressing mechanism may wrongly retain alarms when real bursts occur at the same time in neighbouring areas. However, the statistical chance of simultaneous bursts is very small, and therefore this mechanism will not limit the applicability of the method for the case study described here, but could be an issue for systems with densely interconnected, smaller DMAs. In the Discussion section, under the heading 'Sensitivity analysis model parameters', a sensitivity analysis of the C_{supp} factor is presented.

Performance evaluation

To assess the added value of a burst detection method, both the DP (also noted as true positive rate) and the rate of false

Figure 7 | Real-time water demand monitoring by the detection method. The measured value was continuously compared with the threshold value. At the actual point in time (14:25 h) a burst was detected that started 30 min earlier.

alarms (RF, also noted as false positive rate) need to be evaluated, which can be expressed as (Metz 1978; Jung *et al.* 2013)

$$DP = \frac{\text{number of detected bursts}}{\text{number of days with burst}} \cdot 100\%$$
$$= \frac{\text{True Positives}}{\text{Positives}} \quad (4)$$

$$RF = \frac{\text{number of false alarms}}{\text{number of days without burst}} \cdot 100\%$$
$$= \frac{\text{False Positives}}{\text{Negatives}} \quad (5)$$

Detection methods are only valuable if they are able to identify a substantial part of all bursts, while generating a limited number of false alarms. A third aspect that we think is important to evaluate the performance of a detection method, is the DT. We defined the DT as the average time frame between the beginning and the detection of the burst. A smaller DT value leads to a shorter unawareness period.

The area under curve (AUC) (Hanley & McNeil 1982) of the receiver operating characteristics (ROC) graph (Egan 1975) represents the effectiveness of a detection method: the closer the AUC value to 1 the more effective. The ROC graph depicts the trade-off between the hit rate (true positive rate) and false alarm (false positive rate) of a detection method. We derived the ROC-curve and AUC-value for the burst detection method by varying the C_{lim} value. Note that we applied the DP as true positive rate and the RF as false positive rate. This means that we evaluated 'days' (on which a burst event occurred or not) rather than all

individual 5 min time steps (in which water was flowing from a burst pipe or not) monitored by the method.

RESULTS

Analysis of the reported relatively larger burst events

Detailed information about the exact point in time of beginning, detection, location and isolation of the considered 38 relatively larger burst events was lacking. However, from the flow data information about the running time of the burst could be extracted. The flow patterns of all reported burst events showed a sudden increase at the beginning and a sudden decrease at the isolation point in time. In the intermediate time frame, the water ran freely from the burst pipe. This time frame covers the unawareness period + awareness period + location period + isolation period of the life cycle of a burst (Figure 1). Figure 8 shows the relation between the running time of the burst and the burst flow (left graph) and the start time (right graph).

Figure 8 shows that the running times of most bursts were rather short: 31% were less than 1 h, and 45% were between 1 and 2 h. The isolation period (to identify the proper valves in the geographic information system (GIS), and to locate and close the valves in the field) takes, according to servicemen of Dunea, 30–45 min. Closing the valves of the concerned (large diameter) pipe, requires a long closing time to prevent water hammer. This indicates that most bursts were discovered and reported shortly after they started, resulting in a rather short unawareness period. Figure 8 shows that four bursts had a running time of 6 h
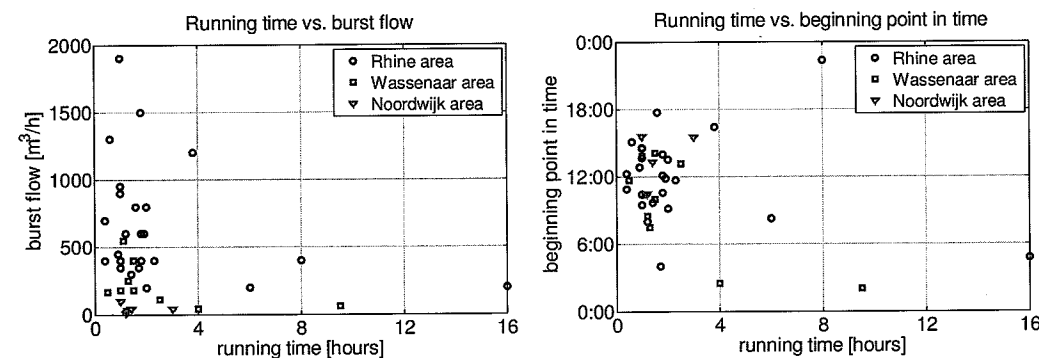

Figure 8 | Relation between the running time of the relatively larger bursts versus the burst flow (left graph) and the running time versus the start time of the bursts (right graph).

or more. These were all bursts that had a low burst flow compared to other bursts, and three out of four started during the night (between 22:00 and 5:00). Assuming the same isolation, awareness and location period, the unawareness period was considerably longer for these bursts. This indicates that bursts that started in the night were not noticed by consumers and not promptly reported to the water company.

Deviations analysis and detection threshold values

Deviations expected water demand

Table 2 shows the percentage of valid values, and the relative and absolute deviations of the expected water demands. It shows that the smallest percentage deviations occurred in the largest area (Rhine area) and the largest percentage deviations in the smallest area (Noordwijk). This is in accordance with the observations reported by Bakker *et al.* (2013b). Meanwhile, the absolute deviations in m³/h were the largest in the largest area and the smallest in the smallest area. This indicates that although the forecasting model performed relatively worse in the smaller areas, still the absolute values of the deviations were smaller, which enabled the detection of smaller bursts.

The signal transformation and deviation analysis, as explained in the Heuristic burst detection method section, was done to derive alarm threshold values. Figure 9 shows the resulting threshold values for the water demand in the Rhine area. The figure clearly shows high threshold values for short moving average time frames and a high expected demand. A high threshold value means that only a large deviation between measured and expected flow (which is
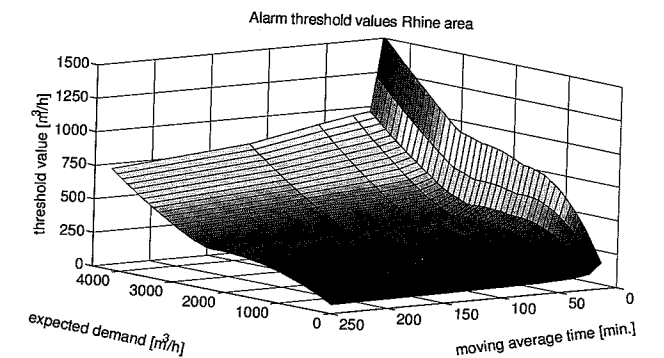

Figure 9 | Alarm threshold values for the expected water demand in the Rhine area.

the case for bursts with high burst flows) will raise an alarm. Lower threshold values occurred when expected demand was lower and/or when the moving average time frames were longer. This means that bursts with a smaller burst flow only raised an alarm when demand was lower (e.g., at night) and/or somewhat longer after the beginning of the burst.

Deviations expected pressure

For eight measured pressures, expected values were generated by applying Equations (1)–(3). Table 3 shows the percentage of valid values, and the relative and absolute deviations of the expected pressures. The table shows that the percentage deviations of the expected pressures were

Table 2 | Percentage of valid values, and deviations of the expected water demands (related to 5 min moving averaged value)

Signal	Valid [%]	Percentage deviation		Absolute deviation	
		SD [%]	5% EP [%]	SD [m³/h]	5% EP [m³/h]
1. Rhine area	100	6.6	11.1	151	254
2. Wassenaar area	100	14.5	25.5	30	53
3. Noordwijk area	100	21.8	36.9	7	11

SD = standard deviation; 5% EP = 5% exceedance probability.

Table 3 | Percentage of valid values, and deviations of the expected pressures (related to 5 min moving averaged value)

Signal	Valid [%]	Percentage deviation		Absolute deviation	
		SD [%]	5% EP [%]	SD [kPa]	5% EP [kPa]
1. Location Cronestein	96.2	0.82	1.13	2.5	3.4
2. Location de Engel	98.4	1.96	2.76	5.9	8.3
3. Location Hillegom	97.2	3.55	4.67	10.4	13.7
4. Location LOI	86.0	0.68	0.94	2.1	3.0
5. Location Meerburg	96.9	0.50	0.66	1.6	2.1
6. Location Noordwijk	93.9	2.50	3.24	7.4	9.6
7. Location Noordwijkerhout	96.8	2.18	3.14	6.8	9.8
8. Location Papelaan	91.8	3.84	6.10	10.8	17.1

SD = standard deviation; 5% EP = 5% exceedance probability.

lower than those of the expected demands (Table 2). This indicates that the pressure could be estimated more accurately, and that relative smaller deviations might be relevant for burst detection.

Performance burst detection method

We derived the initial detection threshold values and the C_{lim} value using the 2007 data. Next, we applied the burst detection method on the 2008–2012 data. We analysed the performance of the method by evaluating the DP and the RF (both related to all observed burst: DP_{All} and RF_{All}; and to the selected subsets of relatively larger bursts: DP_{Larger} and RF_{larger}) and the DT (see Table 4). The table shows that the DP_{All} values were quite low, and lower when the area is larger. The DP_{Larger} values were on average around 80%, the RF values around 3% and the DT values around 20 min. The DT was 5–10 min for most bursts, but a number of bursts was detected much later (the highest DT was 75 min). Figure 10 shows the ROC graph of the burst detection method, applied to the Rhine area. The AUC-value of the curve related to the relatively larger bursts was 0.972 and related to all bursts 0.535. This indicates that in the Rhine area the method was effective for detecting relatively larger bursts, but very ineffective for detecting all bursts.

An analysis of the results showed that all alarms were raised by a deviation of the water demand. During four burst events, a deviation of the pressure raised an alarm as well. During the other events, the deviation of any of the pressures did not exceed the alarm threshold value. This indicates that monitoring the pressures did not provide

Table 4 | Performance burst detection method

	DP_{All} [%]	RF_{All} [%]	DP_{Larger} [%]	RF_{Larger} [%]	DT [min.]
Rhine area (242/24 bursts)	7.8	4.2	79.2	3.4	12
Wassenaar area (26/10 bursts)	25.9	2.3	90.0	2.1	24
Noordwijk area (6/4 bursts)	50.0	2.1	75.0	2.0	20

DP = detection probability; RF = rate of false (related to all burst or to the relatively larger bursts); DT = detection time.
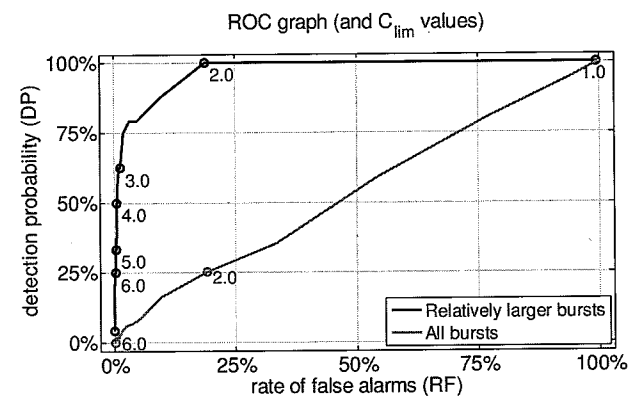

Figure 10 | ROC graphs of the burst detection method in the Rhine area of the relatively larger bursts only, and of all bursts.

additional information for detecting the bursts. This limited sensitivity of pressure sensors (that are at some distance from the burst location), is in accordance with observations in Mounce *et al.* (2011) and Farley *et al.* (2013).

DISCUSSION

Sensitivity analysis model parameters

The C_{lim} factor directly influences the alarm threshold value, and as a result, the factor determines the trade-off between hit rates and false alarm rates. The acceptable number of false alarms can be determined by the water company that uses the method. We aimed at false alarm rate of 3% and analysed the data prior to the monitoring years to find the proper C_{lim} (and C_{supp}) values. It turned out that a C_{lim} value of 2.5 for all areas could be applied, which indicates that this factor is not very sensitive to the size of the monitored area. To assess its influence, we researched different values of the C_{lim} factor. The left graph of Figure 11 shows DP and RF as a function of C_{lim}. The graph shows that a DP of 100% was achieved with a C_{lim} value of 1.8 or smaller. With this value however, a RF of at least 25% occurred. The default C_{lim} value of 2.5 resulted in acceptable DP and RF values. The C_{supp} factor directly influences the threshold value to suppress alarms. The right graph of Figure 11 shows DP and RF as a function of C_{supp}. With smaller values of
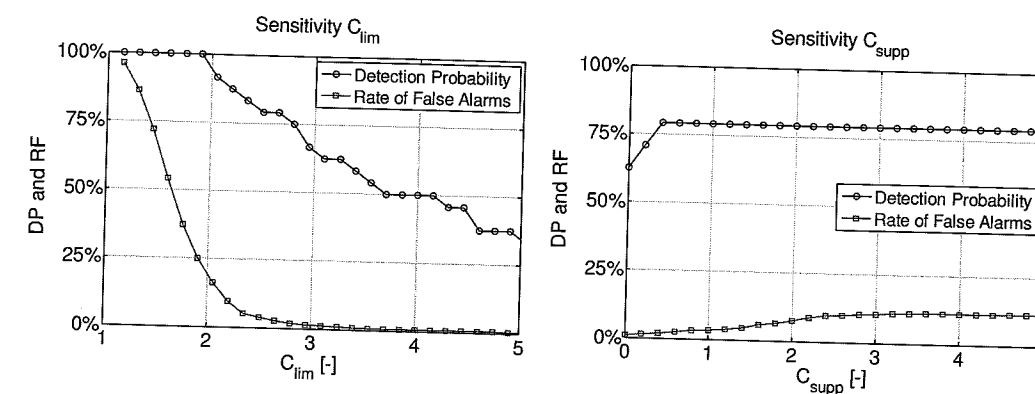
Figure 11 | Sensitivity analysis of the C_{lim} (default 2.5) and C_{supp} (default 1.0) parameters when monitoring the Rhine area water demand, considering the relatively larger bursts.

C_{supp}, more potential alarms are suppressed and the chance of wrongly suppressed alarms increases. The graph shows that the DP decreased at a C_{supp} smaller than 0.5 which indicates that alarms were suppressed wrongly. The default C_{supp} value of 1.0 resulted in acceptable DP and RF values.

Data-driven pressure estimation

We used a data-driven model (Equations (1)–(3)) instead of a hydraulic network model to estimate the pressures. We chose to do so to enable easy and low-cost implementation and to reduce calculation time. However, the data-driven model may have limitations because the pressure regime in the network changes as demand distribution (and flows) through the network change. This might explain why monitoring the pressure proved not to be very valuable for burst detection in our research. However, the pressure estimation was rather accurate: Table 3 shows that the standard deviation was 6 kPa (2.0%) on average. This was more accurate than the demand forecast: the standard deviation of the demand forecast in the Rhine area was 6.6% (see Table 2). A more detailed analysis showed that the maximum pressure deviation at any of the pressure measuring points during the bursts was around 12 kPa for most bursts (4.1% of the average pressure). The average flow deviation caused by bursts was 660 m³/h (22.8% of the average demand). This indicates that the main reason that pressure monitoring was not very sensitive in our research was that the effect of bursts on pressure was much less profound than the effect on the flow.

Applicability of the method

Availability of measurements

We tested the burst detection method on one large and two relatively smaller networks. In the large network, flow and pressure were measured at the main entry point and at eight other locations, and all these measurements were used in the burst detection method. In many other water distribution networks, there are not that many measurements available. The two smaller networks resemble more an average network, where flow and pressure are only measured at one or two locations. The burst detection method proved to be equally effective in the large area as in the two smaller areas. The reason for this is that monitoring the water demand in the area is the key element for burst detection (as explained in the Data-driven pressure estimation section), and the extra information provided by monitoring the pressure is limited. Therefore, the method can be applied to networks where a water balance can be made with flow sensors in (near) real time.

Size of the area

The size of the area that is monitored very much influences the size of the bursts that can be detected. In the large area (Rhine area) only bursts were detected where the burst flow exceeded 150 m³/h; in the smallest area (Noordwijk area) bursts starting at 7 m³/h were detected. This is an important limitation of the burst detection method, and must be borne in mind when implementing the method in larger areas. The

minimum burst size that can be detected in an area can be approximated by calculating the standard deviation of the water demand forecast error. This line of reasoning can also be reversed: if the minimum burst size that must be detected is set at a certain value, the (maximum) size of the areas can be determined. If the existing areas are larger, additional flow meters must be installed to create smaller areas. In such case, additional investments are needed for installing and operating new sensors when implementing the detection method. The further analysis of the relation between the size of the area and the minimum detectable burst size is reported in Bakker et al. (2014).

Changes in operation or topology

Changes in the operation or in the topology of the distribution system can result in changes in the water demand in the area or in the hydraulic behaviour of the network. Because the detection method uses data-driven models to generate expected values of demands and pressures, this deviant behaviour will not be forecasted properly. As a result, false alarms may be expected when the changes in demand and hydraulic behaviour are large. To avoid undesirable false alarms, the burst detection method should be put off-line temporarily in an area, if the operations or topology are changed in this area. The data-driven methods are mainly based on the behaviour of the previous 2–4 days and therefore expected values will be accurate again only days after the change. As a result, the detection can be put on-line shortly after the change in operation or topology of the network.

Testing with off-line data

We tested the burst detection method only with historic off-line data. We used 1 year of off-line data for determining the monitoring threshold values and the method's parameter values. Next, we applied the method to the rest of the historic data in a semi on-line manner. We think, this approach can be applied as well for on-line for monitoring of a water distribution network, provided that 1 year of historic data is available. However, in practice, issues might occur that we have not experienced in the off-line analysis, which might limit the application of the method.

Added value burst detection method

Minimize damage caused by bursts

The running time of most relatively larger bursts (76%) was 2 h or less, and an earlier detection could not have prevented any damage. Four bursts occurred with longer running times of 6 h or more. The burst detection method was able to identify all four events and to raise an alarm. Thus, for these bursts the detection method could have been valuable for the water company, and damage caused by the bursts could have been minimized. As the damage of any single burst can be large, the costs for implementing this burst detection method are likely to compensate the avoided damage.

Need for burst localization

When the detection method detects a burst, the burst pipe needs to be located before it can be isolated and repaired. This can be difficult and time-consuming, especially in the case of a burst in a large area (like the Rhine area). Therefore, the detection method should be combined with a localization method to enable effective response to a burst event. Possible methods to locate a burst are described by, for example, Misiunas et al. (2005a), Farley et al. (2013) and Romano et al. (2013).

Comparison to other burst detection methods

A variety of approaches and techniques has been published for the application area of burst detection. When compared to the results published in other papers, for example, Mounce et al. (2011), Eliades & Polycarpou (2012) and Romano et al. (2012), our method resulted in a shorter DT. A comparison of the DP and the rate of false alarms could not be made because they were defined differently. Furthermore, when comparing our results to the results in other papers it must be stressed that this cannot be done objectively, because our results are primarily based on data from a large area (approximately the size of 20–50 DMAs) where only the relatively larger burst events were evaluated. The other papers present results of monitoring on a DMA scale where all events were evaluated. As far as we know,

no other researchers have studied burst detection techniques at this large scale. The added value of our method is that it uses understandable and easy to use heuristic models to derive expected values and threshold values of the monitored signals that are graphically shown to the user (e.g., Figure 7). Moreover, the method has an effective alarm suppressing functionality that minimizes false alarms caused by abnormal water demands.

CONCLUSIONS

The main assets (treatment plants, reservoirs, boosters and measuring points) of most water distribution systems are equipped with permanent flow and pressure sensors. Currently, the sensors are only used for real time control and management of the water distribution networks. However, the sensors can provide valuable information for detecting abnormal events like pipe bursts. Currently, most (relatively larger) pipe bursts are already reported by consumers shortly after they began, and as a result 76% of all bursts are isolated within 2 h after the start. However, some bursts have a longer running time, and the water flows of those bursts can cause considerable damage to the urban environment. To minimize this potential damage and other negative aspects of pipe burst, an early detection is required.

We developed and tested a heuristic burst detection method off-line on a historic dataset, containing 5 years of hydraulic data in three distribution areas in the western part of the Netherlands. The three areas varied largely in size: 650, 11,180 and 130,920 connections. The data of the latter area contained most burst events, and therefore, this area was dominant in developing and evaluating the method. Due to the large size of this area, only large pipe bursts could be detected, and small size bursts were not detected by the method.

The heuristic burst detection method we propose in this paper is based on monitoring water demands and pressures in the water distribution network. The method uses adaptive data-driven models to generate expected values of the water demands and pressures. Historic deviations between measured and expected values were analysed to set threshold values, and real time observed deviations were

evaluated to raise alarms. The method monitored multiple areas in parallel, which enabled the suppressing of alarms in the case abnormal water demands occurred simultaneously in different areas. The deviation between measured and expected demand was the key element to detect pipe bursts; deviations in pressure appeared to be less valuable for burst detection. As the detection method uses only existing measurements and comprises adaptive data-driven models, it can be implemented and operated at low cost.

When evaluating the method, we considered both all reported bursts and a subset of relatively larger bursts which were selected by applying our (subjective) definition. When all reported bursts were considered, the method detected 7.8% of the bursts in the large area, 25.9% in the medium area and 50% in the small area. When the subset of relatively larger bursts was considered, the method detected around 80% of the bursts in all three areas. The method generated an acceptable number of false alarms, and the average DT was 20 min which is short compared to other burst detection methods. The DT was 5–10 min for most bursts, but a number of bursts was detected much later (up to 75 min). The method was able to detect the critical bursts which had a long running time, at an early stage. This shows that the burst detection method can shorten the 'unawareness period' of a burst, and therewith deliver a contribution to minimize the negative aspects of relatively larger pipe bursts. A further reduction of the negative aspects of bursts can be achieved if the 'location period' can be shortened as well. To achieve this, the burst detection method should be extended with a burst localization method.

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