Detecting pipe bursts by monitoring water demand

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Abstract
An algorithm which compares measured and predicted water demands to detect pipe bursts was developed and tested on three data sets of water demand and reported pipe bursts of three years. The algorithm proved to be able to detect bursts where the water loss exceeds 30% of the average water demand in the area. The accuracy depends on the acceptable number of false alarms By simultaneously running the algorithm in adjacent supply areas, and combining the monitoring results the number of false alarms could be reduced.

Keywords
demand prediction; pipe burst; detection

INTRODUCTION

Unmanned operation of water supply systems

Water supply 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 implies that the distance between the human operator or supervisor and the water production and distribution processes is gradually increasing. This increasing distance results in an increasing risk, that failures in the system will remain unnoticed especially at times when no human supervisor monitors the processes. In water production facilities the equipment (pumps, valves, blowers, et cetera) has failure alerting functionality, which alerts the consigned operator in case of a failure. Distribution networks have no such failure alerting functionality to warn operators in case of a pipe failure. In most distribution networks in the Netherlands, flow and pressure sensors are only installed at pumping facilities and not separately in the pipe networks. The monitoring of these measured flows and pressures is limited to a simple "flat-line" alerting system, of which Mounce *et al* (2010) showed the limitations. As a result many pipe bursts stay unnoticed in the system, and the utilities only take action after customer complaints of low pressure or customers reporting water flows on the streets.

Pipe burst have an important disturbing effect in water supply (Bicik et al (2011)). A pipe burst will not only lead to large water losses, but also to an interruption of water supply to customers and discolouration of the water due to disturbed pipe flows. A pipe burst can also lead to unwanted and unexpected side effects, like flooded basements, road collaps, or a damaged dike in case the water main is next to the dike. To minimise the negative effects of pipe burst an early detection is necessary.

Overview burst detection

For the detection of pipe bursts, various techniques can be used. Puust, *et al* (2010) give a profound overview of different techniques for managing background leakage in distribution systems, as well as detecting pipe bursts.

Monitoring pressure transients
One of the commonly used the techniques for pipe burst detection is based on monitoring pressure transients in the distribution system, which occur after a sudden failure (rupture) of a pipe. By measuring pressure at different locations at a very high sampling rate (2000 Hz, Misiunas *et al* (2005a)) the propagation of the pressure transient in the network can be measured, and the burst location can be approximated. Colombo, *et al* (2009) presents a literature overview of transient monitoring techniques. Brunone and Ferrante (2001), Misiunas *et al* (2005a, 2005b), Kim (2005), Duan *et al* (2011), and Kwon and Lee (2011) present theoretical research to further develop this technique. The technique is only applicable for actual bursts. Pipe failure which develops gradually will not induce a pressure transient, and will therefore not be detected by this technique.

Monitoring flow, or pressure and flow in a DMA
When flow and pressure measurements are present for off-line DMA monitoring, the measurements can be used for on-line monitoring when made available (semi) online. Stephen Mounce researched detection techniques and tested those techniques in a real water supply system in North Yorkshire, UK (Mounce, *et al* (2002), Mounce *et al* (2003), Mounce and Machell (2006), Mounce and Boxall (2010) and Mounce *et al* (2011)). The papers describe the application Artificial Neural Networks (ANN) combined with Fuzzy Logic to evaluate pressure and flow measurements. In Mounce *et al* (2011) the application of the system in practise in a six month test period is described. It was proved that the system was able to detect 7 of 18 reported bursts (11 events missed), where the system generated a total of 46 alerts (39 were not related to actual bursts).

Other promising research in the field of burst detection is carried out by Palau *et al* (2011), who used a multivariable statistical technique (Principle Component Analysis) to derive burst events from flow and pressure data. Bicik *et al* (2011) combined flow and pressure data with information from other data sources, like customer contacts and an hydraulic model to detect burst events. And Khan *et al* (2005) describe the application of experimental failure sensors measuring opacity or temperature for the detection pipe bursts.

Techniques for leak estimation
Poulakis *et al* (2003), Buchberger and Nadimpalli (2004), Aksela *et al* (2009) and Wu *et al* (2010) present techniques for combined background leakage estimation and burst detection, based on measured hydraulic data.

Development deterministic burst detection method
In this paper a pipe burst detection method is proposed, based on an adaptive demand forecasting algorithm in combination with an adaptive threshold monitoring system. The proposed method has some similarities with the method proposed by Misiunas *et al* (2006), which is based on monitoring hydraulic phenomena, and anomaly detection with a cumulative sum function.

MATERIALS AND METHODS

Burst detection by comparing predicted and measured water demand
The developed burst detection algorithm is based on a continuous comparison between the measured water demand and the predicted water demand in an area. The algorithm will process the unfiltered flow measurements for the detection of pipe bursts.

Measured water demand
For each area where the burst detection algorithm is applied, the water demand must be measured. For simple areas the demand is measured directly by the flow meter at the entrance of the area. In more complex areas the readings of a number of flow meters, registering incoming or outgoing flows needs to be combined to calculated the water demand. In case there is a reservoir or a water tower in the area of which incoming and outgoing flow is not measured, this flow has to be calculated. This can be done by integrating the change in the level measurement over time:

$$F_{reservoir,t} \frac{dL}{dt} \cdot A_{reservoir}$$

Predicted water demand
The water demand to each area is predicted by an adaptive demand forecasting algorithm, described in Bakker *et al*. 2003. This algorithm automatically builds up a database with typical curves and factors which characterize the diurnal and weekly patterns of the water demand in the area. The typical curves and factors are used to predict the water demand for the next 48 hours on a quarter of an hourly basis.

Prediction error
The prediction error ($F_{error,t}$) is the difference between the measured flow ($F_{measured,t}$) and the predicted flow ($F_{predicted,t}$):

$$F_{error,t} = F_{measured,t} - F_{predicted,t}$$

In case of a pipe burst, the measured flow will suddenly increase and become higher than the predicted flow. Therefore only positive prediction errors must be monitored in order to detect pipe burst. The positive prediction error ($F_{Poserror,t}$) is derived by:

$$F_{Poserror,t} = \frac{\left|F_{error,t}\right| + F_{error,t}}{2}$$

Dynamic alert threshold
If the positive prediction error exceeds the threshold value during a chosen time window, the burst detection algorithm will generate an alarm. The threshold value is dynamic in time and is calculated at time *t* with:

$$F_{Treshold,t} = C_1 \cdot F_{error,avg} + C_2 \cdot \left(\frac{F_{error,avg}}{F_{meas,avg}} \right) \cdot F_{predicted,t} + C_3 \frac{dF_{predicted,t}}{dt}$$

$F_{error,avg}$ is the average absolute prediction error and $F_{meas,avg}$ is the average measured water demand in the area in the previous year. $dF_{predicted}/dt$ is de derivative of the actual predicted water demand. By calculating the threshold value as function of the predicted demand and the derivative of the prediction, the value is adjusted depending on the accuracy of the prediction: The calculated threshold will be lower when the prediction is known to be more accurate (during low flow and a low derivative of the flow), and higher when the prediction is known to be less accurate (during high flow, and high derivative of the flow). In choosing the constants C_1, C_2 and C_3 a balance must be found between quick and accurate monitoring on the one hand and, limiting the number of false alarms ("ghosts") on the other hand.

Integrating error and threshold over time value
The water demand to an area can be more or less variable. The variability depends highly on the size of the area. In larger areas fluctuations are levelled off, because of limited simultaneity of

individual usages. In smaller areas the levelling off will occur only to a smaller degree, resulting in relatively larger fluctuations. This is especially true in smaller areas where 1 of more (industrial) large consumers are present. Figure 1 shows examples of variability of the water demand in a large, medium and small area. The examples show that not only the percentage of the variation can differ between areas, but also the time scale (the sudden flow increases in the medium area last 5-10 minutes, where the flow increases in the small area last nearly 1 hour).

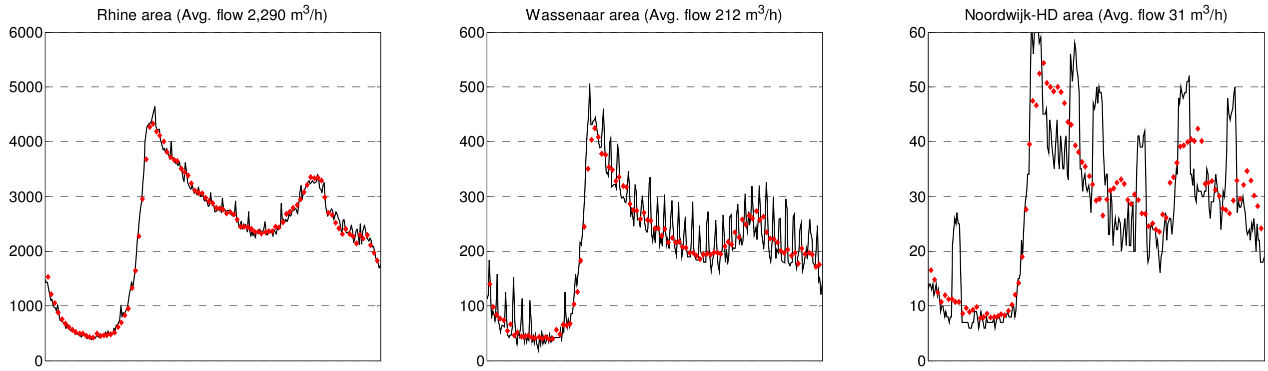

Figure 1. Variability in water demand, in a large area (Rhine area), medium area (Wassenaar area) and small area (Noordwijk-HD area), (– = measured flow, ▪ = predicted flow).

For effective monitoring the variability of the flow has to be taken into account. For this purpose the integral over the monitoring time window (T_{mw}) of both the positive prediction error as well as the threshold are calculated (note that the unit of both derived values is volume (m^3), because flow values (m^3/h) are integrated over time (hour)):

$$V_{Treshold,t} = \int_{t=-T_{mw}}^{t=0} F_{Treshold} \cdot dt \quad and \quad V_{Poserror,t} = \int_{t=-T_{mw}}^{t=0} F_{Poserror} \cdot dt$$

The burst detection algorithm will generate an alarm if the integrated positive error value exceeds the integrated threshold value:

$$Alarm\ if : V_{Poserror,t} > V_{Treshold,t}$$

In other words an alarm will be generated if (over the monitoring time window) the average positive error is bigger than the average threshold. This method enables effective monitoring using the raw measured data, without the need to filter the measurement.

"Dual monitoring": comparison with adjacent area

A potential drawback of monitoring the difference between predicted and measured flow, is that false alarms may be generated when a discrepancy between predicted and measured flow occurs. In many cases the discrepancy is a "systematic error": a similar overestimate or underestimate of the water flow is made in the prediction for all areas where the flow is predicted. This can occur after a sudden change in the weather conditions or the occurrence of special day, which is not modelled correctly in the prediction algorithm. The accuracy of the alarm detection improves when potential alarms are compared between various detection areas. Simultaneous discrepancies between measured and predicted demand indicate a 'demand-event' rather than a burst. An alarm is suppressed when:

$$Alarm\ suppressed\ if : V_{Poserror,adj,t} > C_4 \cdot V_{Treshold,adj,t}$$

C_4 is chosen at a value of 0.3, meaning that a much smaller prediction error in the adjacent zone is enough to suppress the alarm in the monitored zone.

Parallel monitoring for detection of different burst types

Different types of bursts require different settings for C_1 to C_4 and for the monitoring time window T_{mt}. Large bursts are characterised by sudden large increase of the flow, and those bursts need to be detected in a short time frame. Smaller burst are characterised by smaller increase of the flow, and a longer time frame for detection is acceptable. In order to detect multiple types of bursts and minimize the number of false alarms at the same time, multiple burst detection algorithms can be operated in parallel on the same measurement, but with different settings. In this case studt the following settings are used for parallel monitoring:

Table 1. Proposed settings for parallel monitoring to detect both large bursts as well as small bursts

Burst type	C_1	C_2	C_3	C_4	T_{mt}
Large bursts	3	2	0.02	0.3	10 minutes
Small bursts	0	6	0.20	0.3	40 minutes

Case study

Analysis of three areas

For the case study a dataset with historic data was collected. For three areas of drinking water company Dunea, the amount of supplied drinking water in 5 minutes intervals of the period 2006-2011 was collected. Dunea collects and stores all data of pressure and flow measurements in a central database system called EI-Server. As a result of the high reliability of both the meters and the database system, virtually no data gaps of data errors were present in the dataset. The characteristics of the three researched areas are summed in Table 2.

Table 2. Characteristics of the three researched areas (average values of 2009-2011 period)

Area	# properties	Water demand (m^3/h)	Water use m^3/prop/year	# burst incidents
Rhine area	130,920	2,290	145	19
Wassenaar area	11,180	212	154	5
Noordwijk HD area	650	31	391	1

In the Noordwijk HD area there is one customer with (relatively) very high water use. As a result of this high water use of one customer, the average water use per property is in this area approximately 2.5 times higher than in both other zones.

Reported pipe bursts

Dunea makes reports for larger pipe bursts where the burst flow exceeds some 200 m^3/h (pipe diameter 200 mm and larger) since 2009. In the period 2009-2011 a total of 25 larger pipe burst were reported in the tree areas (see Figure 2 and Figure 3).

Simulations

In the case study the prediction algorithm was run using the original data and compared with the actually measured data. After doing the simulations the simulated alerts were compared with the reported pipe bursts. All simulations were carried out with two different settings for the detection algorithm: “loose” with a minimum of false alarms; and “tight” with more false alarms. The settings were constructed by multiplying C_1 to C_3 from Table 1 with 1.0 for “tight” and 1.3 for “loose” monitoring. Because of the higher variability in the water demand in the Noordwijk-HD area, the factors of Table 1 were multiplied by 2 for this area.

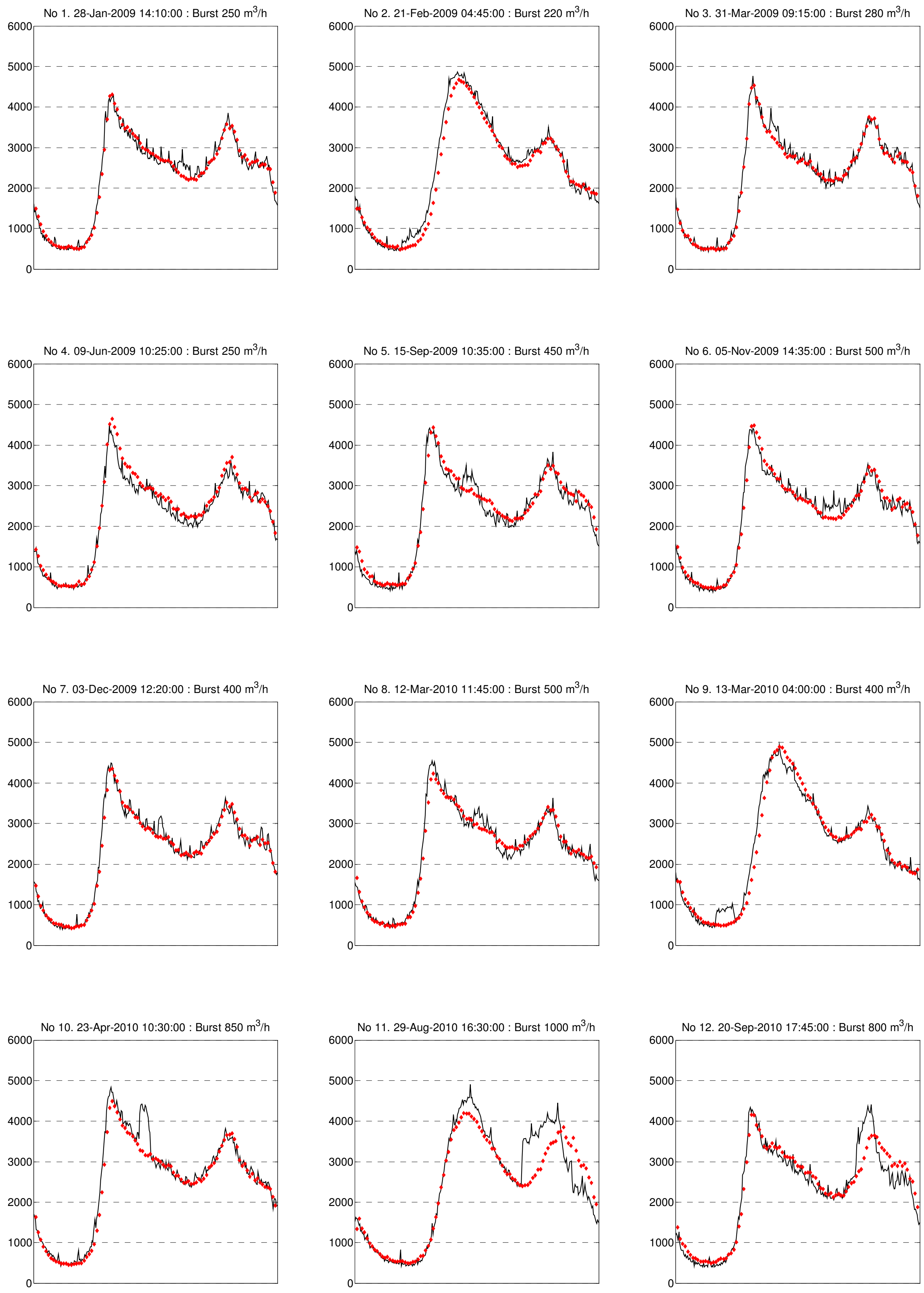

Figure 2. Measured water demand on days with reported pipe burst in 2009-2011 (– = measured flow, ▪ = predicted flow).

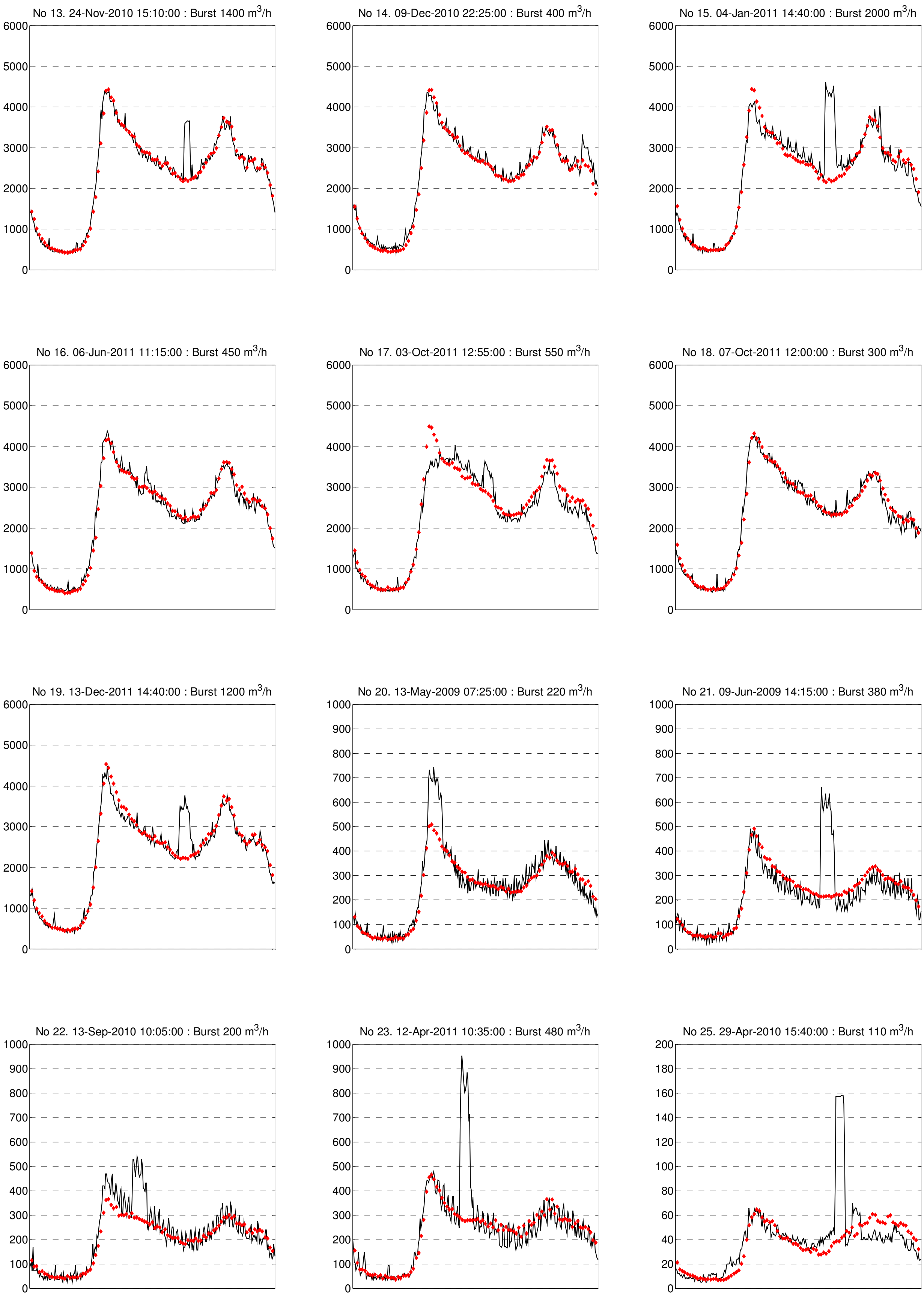

Figure 3. Measured water demand on days with reported pipe burst in 2009-2011 (– = measured flow, ▪ = predicted flow). Note that events 20-23 are in Wassenaar and 25 in Noordwijk-HD area.

RESULTS

The results of the simulations are summed in Table 1.

Table 1. Results of pipe burst detecting algorithm (the table shows the elapsed time between the beginning of the burst and the generated alarm (hours:minutes), X = not detected)

No.	Date burst	Burst flow		"stand alone"		"dual monitoring"	
		m^3/h (% of avg. flow area)		Tight	Loose	Tight	Loose
Rhine area							
1.	28-Jan-09	250	(11%)	X	X	X	X
2.	21-Feb-09	220	(10%)	00:40	X	00:40	X
3.	31-Mar-09	280	(12%)	X	X	X	X
4.	09-Jun-09	250	(11%)	X	X	X	X
5.	15-Sep-09	450	(20%)	X	X	X	X
6.	05-Nov-09	250	(11%)	X	X	X	X
7.	03-Dec-09	450	(20%)	X	X	X	X
8.	12-Mar-10	500	(22%)	X	X	X	X
9.	13-Mar-10	400	(17%)	00:25	00:30	00:25	00:30
10.	23-Apr-10	850	(37%)	00:10	00:10	00:10	00:10
11.	29-Aug-10	1,000	(43%)	00:10	00:10	00:10	00:10
12.	20-Sep-10	800	(35%)	00:15	00:15	00:15	00:15
13.	24-Nov-10	1,400	(61%)	00:05	00:05	00:05	00:05
14.	09-Dec-10	400	(17%)	03:15	03:35	03:15	03:35
15.	04-Jan-11	2,000	(87%)	00:05	00:05	00:15	00:05
16.	06-Jun-11	450	(20%)	X	X	X	X
17.	03-Oct-11	550	(24%)	00:15	X	00:15	X
18.	07-Oct-11	300	(13%)	X	X	X	X
19.	13-Dec-11	1,200	(52%)	00:05	00:10	00:05	00:10
# Bursts 2009-2011 (# detected)				19 (10)	19 (8)	19 (10)	19 (8)
# False alarms per year				30	8	10	2
Wassenaar area							
20.	13-May-09	220	(105%)	0:15	X	1:10	X
21.	9-Jun-09	380	(180%)	0:05	0:05	0:05	0:05
22.	13-Sep-10	200	(95%)	0:10	0:15	0:10	0:15
23.	12-Apr-11	480	(230%)	0:05	0:05	0:05	0:05
24.	9-May-11	80	(38%)	X	X	X	X
# Bursts 2009-2011 (# detected)				5 (4)	5 (3)	5 (4)	5 (3)
# False alarms per year				8	2	5	2
Noordwijk area							
25.	29-Apr-10	110	(330%)	00:10	00:10	00:10	00:10
# Bursts 2009-2011 (# detected)				1 (1)	1 (1)	1 (1)	1 (1)
# False alarms per year				6	0	5	0

The simulations show that a small pipe burst (< 20-25% of the average water demand) generally cannot be detected by the detection algorithm, unless the burst happens during low demand in the night (see burst Rhine area, 21 February 2009). Bursts with flow exceeding 40% of the average demand can always be detected. The detection of bursts between 20% and 40% of the average demand depends on how tight the monitoring algorithm is configured, and at what time of the day the burst occur. When tight monitoring is applied, an unacceptable high number of false alarms occur. Therefore only loose monitoring seems to perform acceptable for practical application. In the Rhine area, the number of false alarms can be reduced by 60-80% by applying "dual monitoring" (rejecting alarms based on comparison with an adjacent zone). For the smaller zones "dual monitoring" doesn't do much about false alarms.

DISCUSSION

Most bursts in this case study started in the daytime, and were promptly observed by customers and reported to the water supply company. The average duration between the beginning of the burst and the isolation of the broken pipe was 2-3 hours. This was without the help of a burst detection algorithm. For those bursts the added value of a detection algorithm would have been limited. However, the bursts on 21 Februay 2009 (No. 2) and on 9 December 2010 (No. 14) started in the evening / night, and were not noticed. As can be observed from the flow data, it took some 8-12 hours before the leaks were isolated. For those bursts the time to repair the pipe could have been shortened if a burst detection algorithm would have been present.

In the case study only information was available of relatively large pipe bursts, and measurements were available for relatively large areas (the Rhine area has the size of 50-100 DMA's). If the flow is measured in smaller areas, also smaller pipe bursts can be detected. In general, smaller pipe bursts will stay unnoticed for longer. The added value of detection of smaller bursts by a burst detection algorithm, is therefore potentially bigger. This can be achieved by installing more flow meters in the distribution network, and monitor the flow with the proposed burst detection algorithm.

CONCLUSIONS

A pipe burst detection algorithm was developed and tested on three data sets of 3 years. Simulations proved that the algorithm was able to detect all pipe burst where the flow exceeds 30% of the average flow in the supply area. An important factor in monitoring the flow, is the number of false alarms which is accepted. False alarms can be reduced by combining the monitoring of two adjacent areas.

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