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Event detection with combined sensors in the distribution network of Groningen

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Event detection with combined sensors in the distribution network of Groningen

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Managementsamenvatting

Optimale plaatsing van druksensoren toegevoegd aan een bestaand sensornetwerk in Groningen

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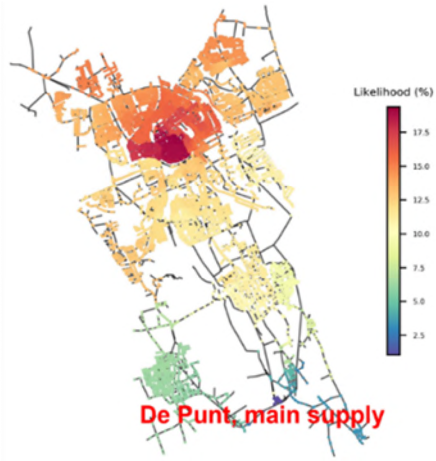
Sensoren kunnen helpen bij het bewaken van drinkwaterdistributienetwerken en afwijkingen van de normale werking van het systeem detecteren. Waterbedrijf Groningen heeft een pilotgebied ingericht met zeven gecombineerde sensoren voor elektrische geleidbaarheid (EC) en druk. Om een mogelijke uitbreiding van het sensornetwerk te onderbouwen en het ontwerp en de voordelen te onderzoeken, is een gevoeligheidsstudie uitgevoerd op basis van simulaties met hydraulische leidingnetmodellen. Deze geeft inzicht in het vermogen van sensornetwerken van verschillende vorm en grootte om afwijkende gebeurtenissen (‘events’) te detecteren, zoals lekkages, afsluitingen en afwijkende verhoudingen van de leveringsvolumes vanuit twee pompstations. Lekkages blijken gemakkelijker te detecteren dan afsluitingen en events worden gemakkelijker gedetecteerd door EGV- dan door druksensoren. Eventdetectie met EGV-sensoren is bovendien meer locatiespecifiek dan met druksensoren. Een voorwaarde is wel dat er menging optreedt van verschillende waterkwaliteiten vanuit verschillende bronnen, wat niet altijd en overal het geval is. De locatie van 15 aanvullende druksensoren is geoptimaliseerd voor de gecombineerde detectie van lekkages en afsluitingen. De aanbeveling van dit onderzoek is om op deze locaties druksensoren te installeren en daarmee praktische kennis op te doen over de werking van het systeem en de detectie van events.



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Proefgebied Groningen toont de detectiekans van lekkages en afsluitingen op basis van drukafwijkingen boven een drempelwaarde van 0,5 meter waterkolom

Belang: onderbouwen van toevoegingen aan bestaand sensornetwerk voor eventdetectie

Een klein deel van de afsluiterstanden in Nederlandse distributiesystemen is onjuist geregistreerd. Dit kan de werking van het systeem negatief beïnvloeden, bijvoorbeeld doordat verblijftijden afwijken van de verwachtingen of doordat reparaties of werkzaamheden worden vertraagd. Dit heeft (ongeplande) ondermaatse levering en ontevreden klanten tot gevolg. De mogelijkheden om het systeem te monitoren zijn vaak beperkt vanwege de ontoegankelijkheid van het ondergrondse netwerk, maar gebruik van sensoren biedt nieuwe mogelijkheden. Waterbedrijf Groningen (WBG) heeft daarom eerder een deel van het netwerk in Groningen ingericht als pilotgebied voor monitoring met sensoren. In dit deelgebied met 946 km leiding zijn op dit moment zeven sensoren geïnstalleerd die tegelijkertijd de druk en het elektrisch geleidingsvermogen (EGV) meten. Door naar de gevoeligheid van EGV- en druksensoren voor operationele gebeurtenissen te kijken, kan worden onderzocht of toevoeging van extra sensoren zinvol is en in welke configuratie dat de meeste voordelen biedt voor eventdetectie.

Methode: netwerkberekeningen gericht op inzicht in ontwerp van aanvullend sensornetwerk

Om de relatie tussen sensordichtheid en eventdetectie voor sensornetwerken met EGV- en druksensoren beter te begrijpen, is een gedetailleerde gevoeligheidsstudie uitgevoerd met hydraulische modelberekeningen van het pilotgebied in Groningen. Daartoe is een groot aantal modelscenario's van drie soorten events (lekkages, afsluitermutaties en verdeling van leveringsvolumes) gesimuleerd. Synthetische sensorsignalen in scenario's met en zonder events werden met elkaar vergeleken, waarbij de discrepantie als maatstaf dient voor het bepalen van detecties. Met een gevoeligheidsanalyse is gekwantificeerd hoe extra sensoren de detectiekansen verhogen en is het belang van sensorlocaties geduid. Een optimalisatie-algoritme is gebruikt voor de locatiebepaling van 15 extra druksensoren, volgens specifieke criteria en randvoorwaarden.

Resultaten: gevoeligheidsanalyse toont grootte en optimale plaatsing aanvullende sensoren

De modelresultaten laten zien dat lekkages makkelijker worden gedetecteerd dan afsluitingen en dat (alle typen) events makkelijker worden gedetecteerd door EGV- dan door druksensoren. Eventdetectie met EGV-sensoren is bovendien meer locatiespecifiek dan met druksensoren, waarschijnlijk vanwege (en op voorwaarde van) lokale verstoringen in de mengzone die signalen in EGV sterker beïnvloeden dan de druk.

Voor hogere sensordetectie-drempelwaardes (respectievelijk 0,1; 0,3; 0,5 meter waterkolom) neemt met druksensoren de berekende maximale detectiekans af voor gemodelleerde lekkages (van 36% naar 12% naar 8%) en afsluitingen (19% naar 7% naar 4%). Het toepassen van een drempelwaarde beperkt dus de prestaties, maar is in een echt netwerk noodzakelijk om vals-positieve detecties te voorkomen, bijvoorbeeld vanwege signaalruis.

Het verhogen van het aantal (aanvullende) druksensoren verhoogt de detectiekans, maar bij elke toevoeging wordt dat effect kleiner: de eerste 30 extra sensoren dekken ongeveer 2/3e van de maximale waarschijnlijkheid die zou worden bereikt met 1000 sensoren in het netwerk. Resultaten van 1000 randomiseringen van 15 aanvullende druksensoren tonen het belang van optimale plaatsing: een toename van de gemiddelde naar de maximale detectiekans is ongeveer vergelijkbaar met een verdubbeling van het aantal sensoren (van 15 naar 30).

De optimale configuratie van 15 extra druksensoren is berekend voor verschillende instellingen van de detectiedrempel en het optimalisatiecriterium. Deze aanpak biedt een "menu" van sensorconfiguraties waaruit het waterbedrijf kan kiezen, afhankelijk van de gekozen focus bij het uitbreiden van een bestaand sensornetwerk.

Implementatie: uitbreiden van pilotgebied voor begrip eventdetectie met praktijkmetingen

Aanbevolen wordt om 15 extra druksensoren te installeren in pilotgebied Groningen op de in dit onderzoek geoptimaliseerde locaties. De ontwikkelde methode moet worden aangepast aan een echte distributieomgeving, inclusief systeemruis en imperfecte metingen. Door gebeurtenisscenario's in het echte netwerk te testen met (gesimuleerde) lekkages, afsluitingen en leveringsafwijkingen is het mogelijk sensornetwerken te evalueren op eventdetectie met praktijkmetingen. Dit biedt een aanvulling op de theoretische inzichten die in dit onderzoek zijn gevonden.

Rapport

Dit onderzoek is beschreven in het rapport "E*vent detection with combined sensors in the distribution network of Groningen"* (BTO-2023.031).

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Contents

1 Introduction

A small part (approx. 1%) of valve positions in Dutch distribution networks are known to be incorrectly registered, and pipeline leaks or unintentional anomalies in supply sometimes occur. Such events can negatively affect the supply of drinking water and the utilities' capacity to intervene: residence times, locations of mixing zones and flow reversals can deviate from expectations, and the necessary closure of pipeline sections in case of calamities can be hampered and contribute to customer minutes lost (CML) and dissatisfied customers. An obstacle to properly assess operational conditions is the limited extent to which pipeline networks are usually monitored, but the application of sensors offers new opportunities.

In the current, overarching Joint Research Programme (BTO) project "Smart Water Networks" several pilot studies are being conducted to investigate how smart networks can be realized with water meters and sensors in the distribution system through the application and integration of various data sources and models. The aim is to investigate how the wide application of (combined) sensors can lead to a more reliable, efficient and transparent drinking water supply. The focus of the BTO project is explicitly not on the practical aspects of installing sensors, choosing a technique or data protocol, putting the data quality in order or setting up ICT, but on the application of the data obtained from the sensors in the pilot and data aimed at the operation of the pipeline network.

In previous BTO research, knowledge has been gained about developing a sensor network for data-driven operations (Vonk & Vries, 2016). The areas of interest included the selection of the right type of sensor, a cost-benefit analysis of a sensor network (Van Summeren, 2016), and a design process using advanced optimization techniques. It has also been investigated how sensor signals can be analyzed for detecting deviations from normal operation (Vries & Van Summeren, 2017). Electrical conductivity (EC) proved to be a useful parameter, because water types that originate from different sources can be distinguished based on EC and thus provide insight in (deviating) water supply (Van Summeren et al., 2018).

Waterbedrijf Groningen (WBG) maintains a pilot area that can serve as a test environment for model calibration and network monitoring with sensors. In the distribution area of the city of Groningen, WBG has installed sensors that continuously measure EC, pressure and temperature (Van Summeren & Hillebrand, 2019). The pipeline network has an open structure of mainly looped but partly branched network sections and is representative of pipeline networks of many large and medium-sized cities in the Netherlands. In two previous BTO projects, a methodology was developed to investigate whether differences in measured and modeled EC and pressure signals could be related to (unscheduled) operational conditions (Van Summeren & Hillebrand, 2019; Van Summeren & Castro Gama, 2020). To this end, the pipeline network model was adapted to the actual conditions of the evaluation period (June/July 2019) in which two unexpected circumstances occurred: a large culvert leakage and unintended transit supply from the city outskirts of Hoogkerk. Based on a comparison of differences between known and measured sensor signals, it was shown that with the followed approach the combined measurement of EC and pressure has an added value and that the culvert leak and transit supply are both detectable (Van Summeren & Castro Gama, 2020).

These previous findings resulted in additional questions regarding the design and benefit of sensor network design, in order to justify possible adoption for drinking water companies. To obtain a better understanding, it was recommended to investigate

i. the sensitivity of EC and pressure sensors to operational events in order to provide a substantiated estimate of the number and type of sensors needed to detect such events;

ii. the automatic updating of distribution network models with on-line data from pumping stations and interventions such as cleaning actions and construction work; and

iii. the reliability of sensor measurements.

The current study focuses on recommendation number (i) above. More specifically, the main objectives are:

a) to determine the relationship between the density of sensors (expressed in number of sensors in the Groningen pilot network of 946 km) and the resolving power of the sensors for unexpected operational conditions, expressed as a likelihood of event detection; event localization is outside of the scope of the current study;

b) to determine the added value of combining EC and pressure measurements.

To this end, three types of event scenarios (valve mutations, leakage, partitioning of supply volumes) were simulated using the hydraulic network model of Groningen. Synthetic pressure and EC responses to these events were calculated (relative to a reference scenario without an event) and used to quantify the performance of sensor networks of various sensor number and sensor type. Although the present study is theoretical in nature, i.e. no field measurements were used, its purpose is clearly aimed towards practical application by:

- quantifying the expected benefits of a sensor network in terms of event detection;

- demonstrating the placement of pressure sensor at preferential locations in the distribution network of Groningen for one or more specific purposes.

2 Method

2.1 Hydraulic network model of the city of Groningen

The hydraulic network model of the city of Groningen underlies the network analysis of this research. The model for the year 2019 was exported from InfoWorks and provided to KWR by Waterbedrijf Groningen (Figure 1). It has a total pipe length of 946 km and consist of 35,634 junctions, 32,699 pipes, and 4,084 valves (throttle control). In the 24 h model the total demand was partitioned among demand nodes subject to 19 different demand pattern, allocated on the basis of their specific function (household, industrial, hospital, etc.). In accord with the period that was evaluated, the model contained three supply locations (Figure 2). The main supply (De Punt, “DP”) was modeled as a fixed-head reservoir (“DP1”, total head pattern 31.87 m) in combination with a prescribed flow supply (“DP2”, modeled as a time-dependent negative demand node). The support supply was from transfer point Ruisscherbrug (“RB”), in which the flow was prescribed as a time-dependent pattern.

The pressure in the network model was controlled by the fixed-head reservoir at De Punt. This deviates from the real-life situation in which the reservoir pressure adjusts in real-time to the system pressure (for which the minimum recorded value of pressure loggers at several locations in the city center of Groningen is considered). Thus, the modeled supply pressure did not realistically respond to system pressure variations at the logger locations, for example in case those pressure levels are affected by a leakage event. Although this can cause a deviation of the absolute system pressure compared to the real-life situation, the influence on temporal and spatial pressure *variations* (on which the event detection approach was based) is expected to be small for the medium-sized events considered in this study.

The EC at supply locations De Punt and Ruisscherbrug was taken constant at 507 µS/cm and 377 µS/cm, respectively. These values are the average values of recorded EC-values in the summer period of 2019. The real-life EC signals showed a (double-bandwidth) variation of roughly 50 µS/cm. The variation of the two signals is largely uncorrelated (Van Summeren & Hillebrand, 2019). Exceptions are those times when Ruisscherbrug is not supplying, and the measurement location receives water from De Punt and, consequently, records EC-values close to those recorded at De Punt.

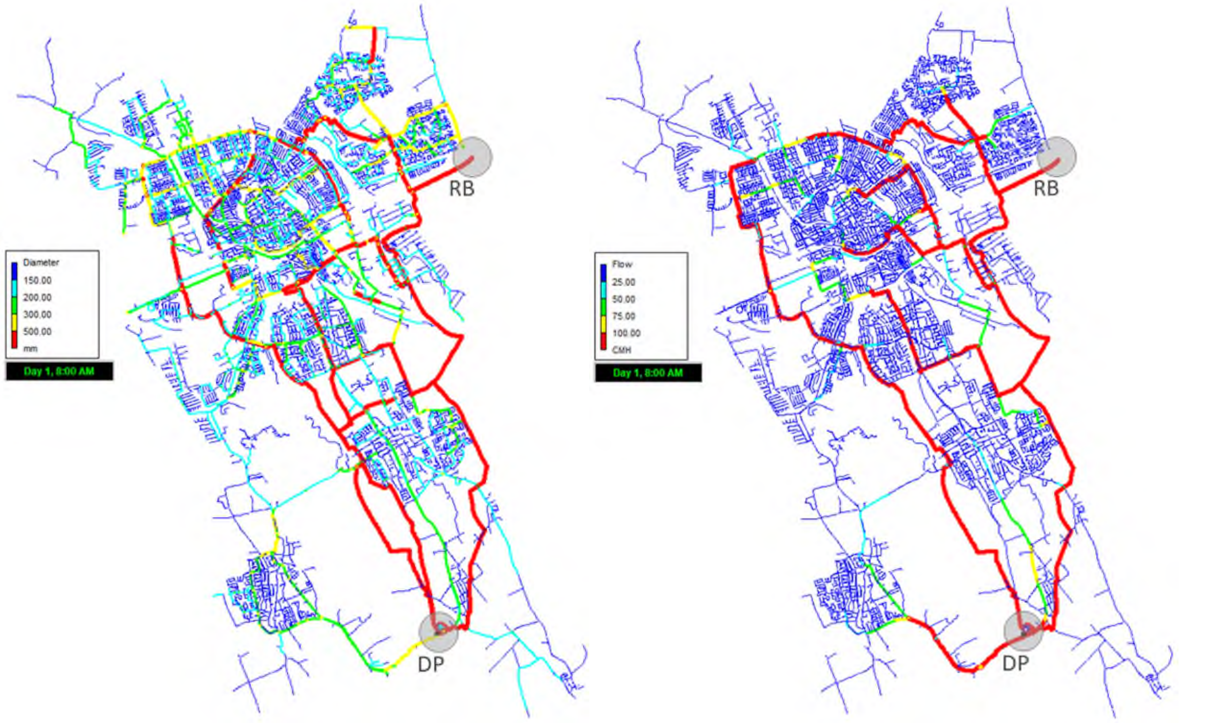


Figure 1. Hydraulic network model of the city of Groningen, representative for the year 2019, showing (left) diameters (in mm) and (right) flow (in cubic meters per hour) at 8AM. Grey circles show the supply zones De Punt ("DP") and Ruisscherbrug ("RB").

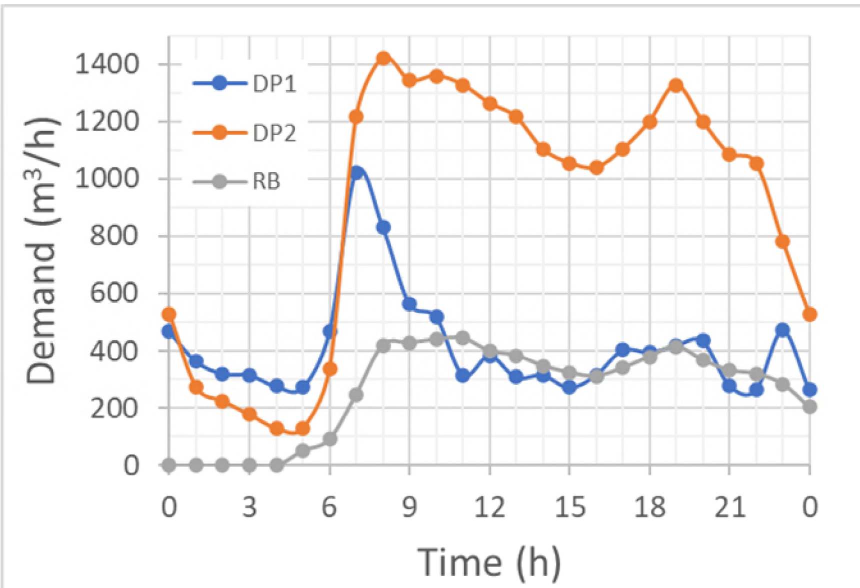


Figure 2. Supply pattern in the Groningen model of production location De Punt ("DP1"and "DP2") and support supply Ruisscherbrug ("RB").

2.2 Event detection metrics

In this study, event detections of virtual sensors were calculated using one *reference* scenario that represents the standard operation of the hydraulic network plus a series of *event* scenarios. Each event scenario deviates from the reference scenario by a single event only. The events comprise of leaks, valve mutations, and supply volume partitioning (see Section 2.3). At evaluation locations, the anomalous sensor signal in response to the event was calculated as the difference in sensor signal (pressure or EC) between event and reference scenario.

The *sensor event response* (or '*impact*') at an evaluation location was calculated as the time during an evaluation period in which the difference between scenario and reference case was larger than the *sensor detection threshold* (Figure 3). The sensor *detection threshold* differs from the sensor *detection limit*, which is a feature of the sensor. The detection *threshold* was defined as the minimum below which an event is assumed to remain undetected. The purpose of using a threshold was to exclude sensor signal that cannot be reasonably distinguished from "non-events". Such non-events or system noise may for example be caused by stochastic demand variations and unscheduled pump operations. Without applying a detection threshold, more events would be detected, but would also result in many false positive detection events.

The sensor detection thresholds considered were based on real-life measurements at the seven sensors in the pilot area and during the 2019 evaluation period. Based on real-life measurements, the signals include daily variations in system operation, including stochastic demand variations. For pressure, threshold values of 0.1, 0.3, and 0.5 MWC were considered, based on the standard deviation of around 0.4 to 0.5 MWC (fairly uniform over time and across the seven locations). These values are well above the precision (0.01 MWC) and accuracy (estimated as 0.015 MWC) of the sensor (Van Summeren & Hillebrand, 2019).For EC, detection threshold values of 10 and 50 µS/cm were considered – taken somewhat arbitrarily as a substantial fraction of the EC-difference of 130 µS/cm between the water types supplied by the main (De Punt) and support supply (Ruisscherbrug). This is above the precision (1 µS/cm) equal to or above the accuracy (1% of the measurement with a minimum of 10 µS/cm) of the EC-sensor.

The evaluation period was chosen as 24 h for both pressure and EC. For pressure the evaluation period starts directly after the event onset (because pressure responds almost instantly to simulated events). In contrast, for EC the evaluation period starts 3 days after the event, because EC responds with a delay as it is carried by the water from the event to the sensor location. Three days is sufficient to cover the maximum residence time in the Groningen network (approximately 72 hours). The time fraction of the 24 h evaluation period in which the signal anomaly surpasses the sensor detection limit is referred to as the *exceedance time*. It can be seen as the response of a particular sensor to a particular event. The Chama package (Klise e.a., 2017) is used to calculate the exceedance times. A so-called *impact matrix* depicts exceedance times (sensor response values) for all combinations of sensor locations and event locations.

The *event detection* of an individual sensor is a binary value; it equals 1 when the anomaly exceeds a sensor detection threshold at any time during the evaluation period and 0 otherwise. The *detection likelihood* is calculated as the ratio of positive event detections to the total number of event scenarios tested.

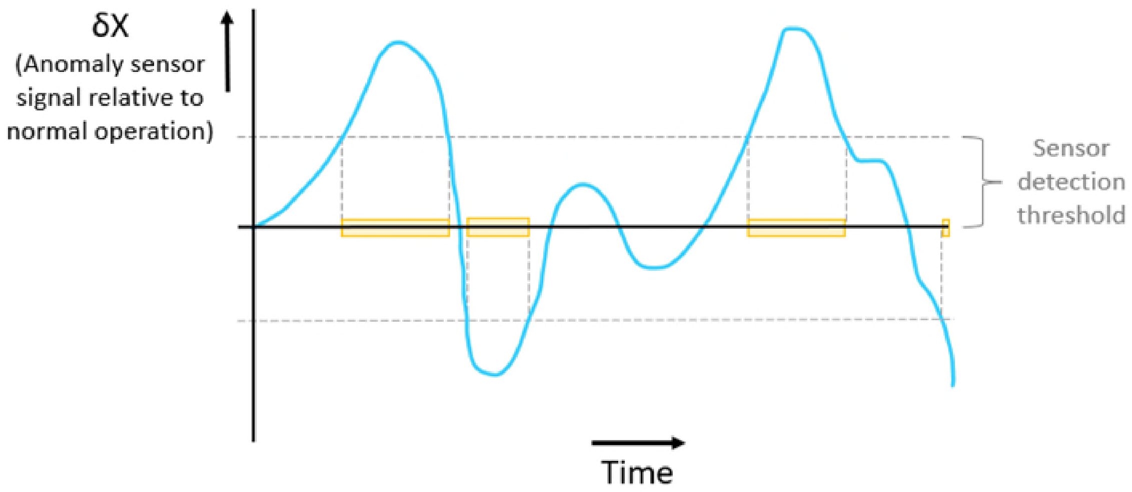


Figure 3. Schematic illustration of sensor detection at an evaluation location in the hydraulic network. The blue curve represents the sensor signal deviation of an hydraulic event scenario relative to standard operation (δX). The orange bins represent times of positive event detection.

The detection of a sensor *network* (as opposed to individual sensors) to a single event is assumed successful when at least one of the sensors in the sensor network detects the event during the evaluation period (disjunction; OR-operation). The *event detection likelihood of a sensor network* is calculated as the number of scenarios with a positive detection relative to the total number of scenarios tested. A likelihood of 0 and 1 signifies a sensor network detection of *no* events or *all* events, respectively.

2.3 Event scenarios and sensor locations

Three sets of *event scenarios* were generated using the *EPANET*-based *WNTR* software package (Klise, et al., 2018):

- *Leakages*: 1000 leakage scenarios were generated with randomly placed dynamic leakages assigned to pipes of diameter greater than 150 mm. Each leakage was simulated as a full pipe break, following the leakage formulation used by WNTR, based on Crowl & Louvar (2011). In general, the leakage rate increases with the pipe diameter, as shown in Figure 4.
- *Valve mutations*: 1000 valve scenarios were generated in which the status of a randomly selected valve within the 100 to 300 mm diameter range was changed from “open” to “closed”. Valve closures that cut off any demand nodes were excluded from the analysis.
- *Supply anomalies*: in 8 scenarios the fractionation of the supply between De Punt and Ruisscherbrug pumping stations was altered (from -40% to +40% in steps of 10% relative to the reference model). This was achieved by scaling the (flow-controlled) supply at Ruisscherbrug. In the chosen model set-up the total demand is met because the pressure-controlled supply at De Punt compensates automatically for the altered supply at Ruisscherbrug.

A set of *candidate sensor locations* were randomly selected from pipes with diameters between 100 and 300 mm – a reasonable range to expect a substantial hydraulic impact, but without a substantial impact on the network operation when installing the sensors. A *sensor network* consists of a random *subset* of the pre-selected candidate locations.

In making the trade-off between calculation times and accuracy, this study draws from previous BTO research that showed that, for event locations, a relatively small sample (ca. 100 locations for a network model of comparable size: Leeuwarden) from all network nodes suffices to calculate representative detection likelihoods. However, for sensor locations a too strict limitation of the number of potential sensor locations comes at the risk of excluding valuable locations from consideration (Van Thienen, 2014). However, the referenced study investigated only (synthetic and generic) water quality sensors. Although this provides a starting point, some caution has to be taken when applying the results. This motivated the choice to limit the number of event scenarios to 1000 throughout this study and the number of potential sensor locations initially to 1000 (in Section 3.2) and subsequently to 25,000+ (in Section 3.3).

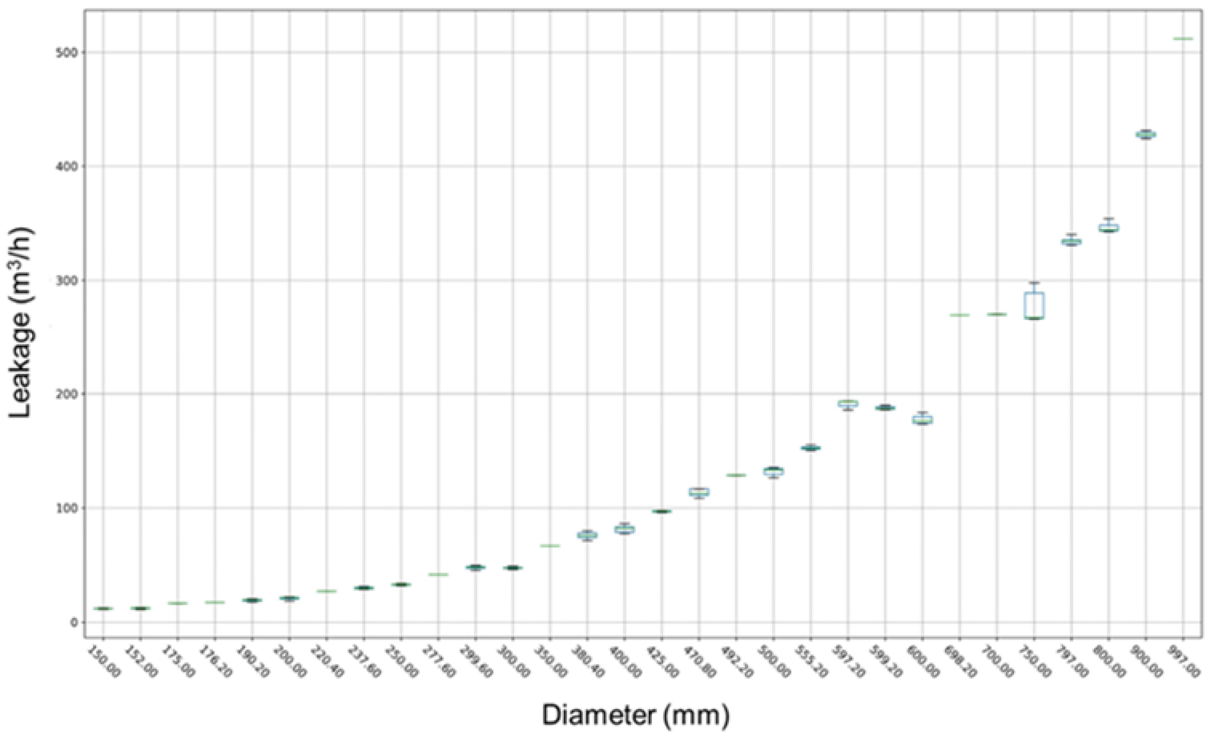


Figure 4. Relationship between leak pipe diameter and resulting leakage rate, assuming a full pipe break.

2.4 Sensor location optimization

Optimal sensor placement for the purpose of detecting leakages and/or valve mutations is determined using the coverage-based optimization formulation, based on the p-median facility location problem. The p-median problem is useful in many real world situations such as optimizing the location of industrial facilities or warehouses (Cristofides (1997); Hansen & Jaumard (1997); Krarup & Pruzan, 1983), to place sensors in large water distribution networks (Berry e.a. (2006); USEPA12; USEPA15), and for gas detection in petrochemical facilities (Legg et al. (2012)).

In the p-median problem, p facilities (e.g., central warehouses) are to be located on m potential sites such that the sum of distances d_{aj} between each of n customers (e.g., retail outlets) a and the nearest facility j is minimized. In comparing the sensor location and p-median problem, there is an equivalence between (1) sensors and facilities, (2) scenarios and customers, and (3) event impacts and distances. The p-median facility location problem is described mathematically as:

$$
\begin{aligned}
&\text{minimize} && \sum_{a\in A}\alpha_a\sum_{i\in\mathcal{L}_a} d_{ai}x_{ai} && \\
&\text{subject to} && \sum_{i\in\mathcal{L}_a} x_{ai} = 1 && \forall a\in A \\
& && x_{ai}\le s_i && \forall a\in A, i\in\mathcal{L}_a \\
& && \sum_{i\in L} c_i s_i \le p && \\
& && s_i\in\{0,1\} && \forall i\in L \\
& && 0\le x_{ai}\le 1 && \forall a\in A, i\in\mathcal{L}_a
\end{aligned}
$$

Where:

A is the set of all scenarios
L is the set of all candidate sensors
$\mathcal{L}_a$ is the set of all sensors that are capable of detecting scenario a
α_a is the probability of occurrence for scenarios a
d_{ai} is the impact assessment, and represents some measure of the impact that will be incurred if scenario a is first detected by sensor i
x_{ai} is an indicator variable that will be 1 if sensor i is installed and that sensor is the first to detect scenario a (where first is defined as the minimum possible impact, usually defined as time to detection)
s_i a binary variable that will be 1 if sensor i is selected, and 0 otherwise
c_i is the cost of sensor i
p is the sensor budget.

The approach to solve the optimization is Greedy Randomized Adaptive Search Procedure. This approach is used to generate a set of high-quality solutions using biased greedy construction techniques. Steepest-descent hill-climbing is then used to move from each of the resulting solutions to a local optimum. Finally, path relinking is used to further explore the set of solutions lying at the intersection of the resulting local optima (Resende and Werneck 2004). In this study, we use Python package Chama (Klise e.a., 2017), which is developed by Sandia National Laboratories and the U.S. Environmental Protection Agency. This package was developed to be a general purpose sensor placement optimization software tool. It includes mixed-integer linear programming formulations to determine sensor locations and technology that maximize the monitoring effectiveness. The above -mentioned optimization method is integrated in Chama. The Chama package provides the functionality to define the sensor technology and characteristics, e.g., fixed point or moving point sensor location, and the cost of each sensor. We applied the stationary point sensor, and assigned the same cost for all sensors as 1. Then, the total sensor budget equals to the total amount of sensors. In this research, we did not constrain the optimization with the total sensor budget.

3 Event detection with Groningen's sensor network

3.1 Introduction

The analysis described in this chapter consists of two main parts. The first part (Section 3.2) contains a sensitivity analysis to determine the pressure and electrical conductivity (EC) response to three event types (leakages, valve mutations, and supply anomalies). It is also determined how the sensor detection likelihood depends on the location in the network model. The second part (Section 3.3) is specific to pressure sensors only (no EC) and leakages and valve events only (no supply events). This part contains a more in-depth analysis of the sensor response with respect to the number of sensors, sensor detection threshold, and the pipe diameter of sensor locations. It also compares the performance of a network of optimized vs. randomly placed sensors. Finally, this section describes the placement of 15 pressure sensors in the Groningen network (in addition to 7 previously installed sensors) optimized to detect leakage and/or valve events. Pressure sensors were chosen over combined EC and pressure sensors because more sensors can be purchased for a given budget (combined sensors are roughly 10 times more expensive than pressure sensors). For this reason, the second part of the analysis focuses on pressure sensors only (Section 3.3). Although the sensitivity analysis and pressure sensor placement are site-specific applications to the city of Groningen, the *approach* is generally applicable to distribution networks in other locations.

3.2 Sensitivity of pressure and electrical conductivity to leakage events, valve mutations, and supply anomalies

Figure 5 and Figure 6 show the pressure and EC response of one (simulated) leakage event in the Northeast of the network model. In this example (as for most other event-sensor combinations) the pressure and EC appear very similar for the scenarios with and without an event (cf. panels (a) to (b), and (d)). The signal *differences* ("with" minus "without") are readily distinguished (panels (c) and (e)), but have small amplitudes: in the order of 1/1000th of the system pressure and 1/10th of EC levels.

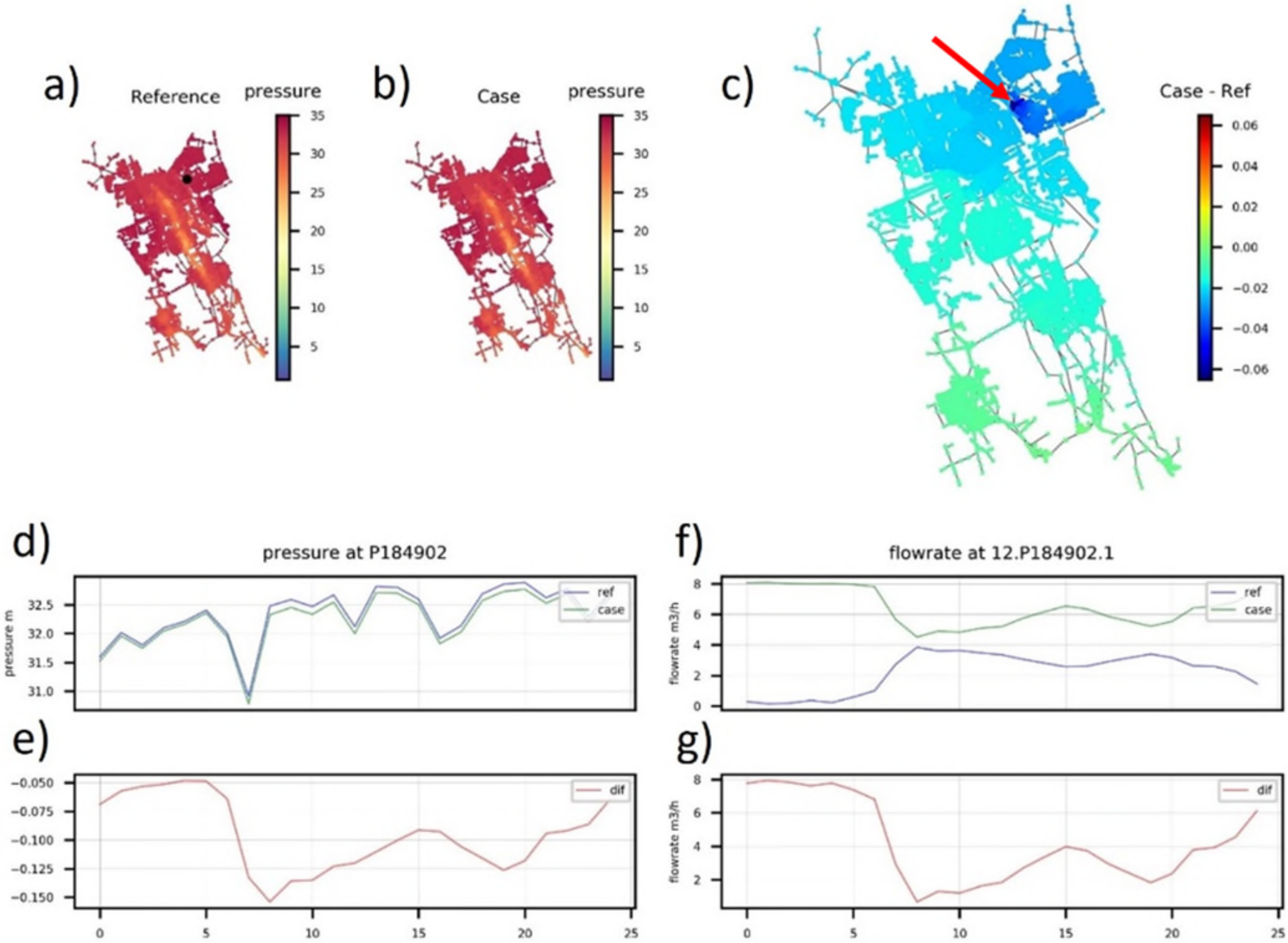


Figure 5. Calculated sensor response of a leakage event at pipe 12.P184902.1 (indicated by the red arrow in panel (c)). Snapshots of system pressure of the reference model (a) without and (b) with the leakage, and (c) the pressure difference ("with" minus "without"). Time series of (d) the pressure in the reference scenario (blue curve) and event scenario (green curve), and (e) the difference. Panel(f) and (g) are the same as (d) and (e), but for the flow rate. The evaluation location (node P184902) is adjacent to the event location (pipe break at pipe P184902.1).

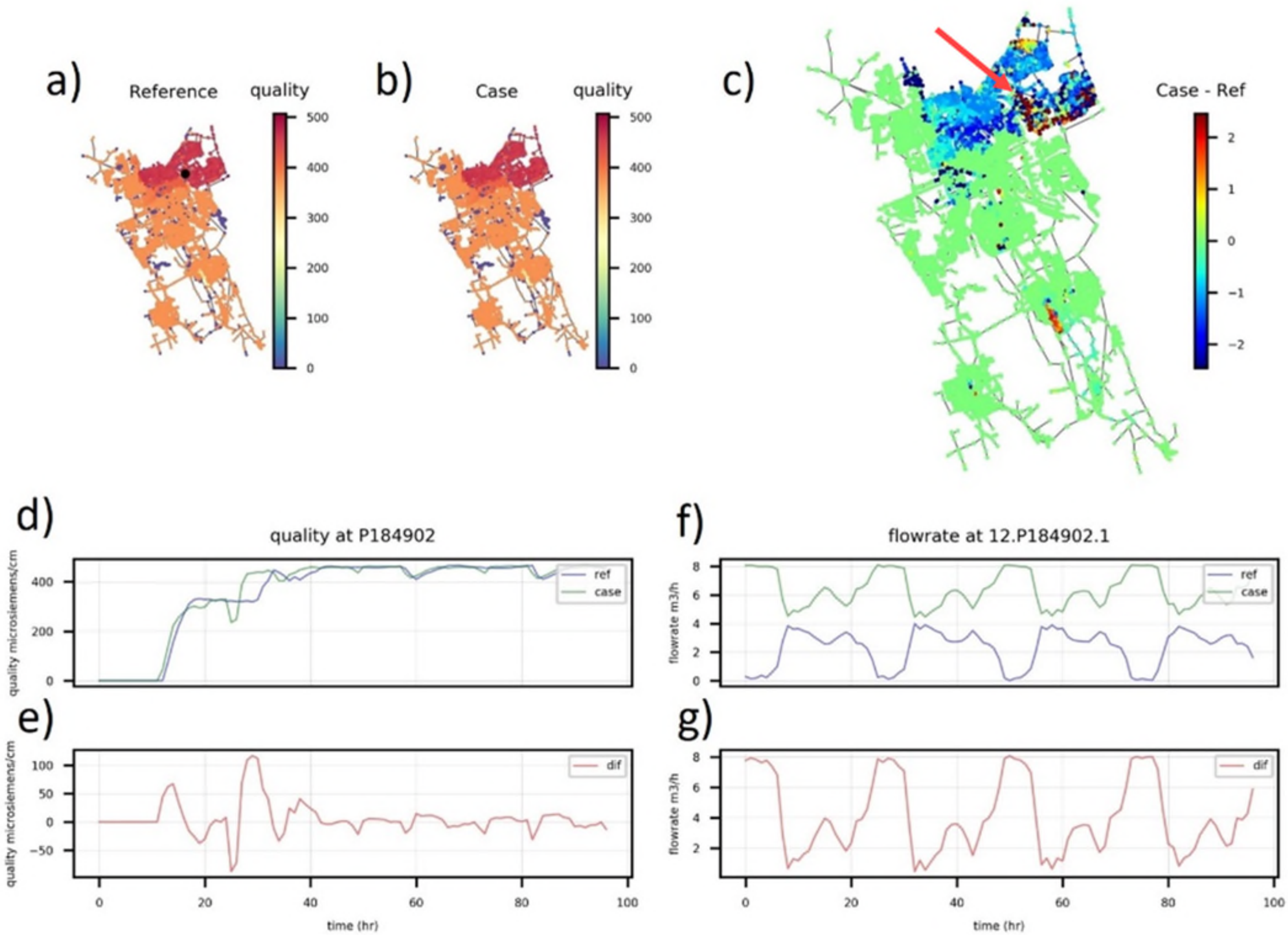


Figure 6. Same as Figure 5 but for EC instead of pressure. The evaluation period is the fourth day: 72 to 96 hours.

3.2.1 Pressure response to leakages, valves mutations, and supply proportion

The example in the previous section is helpful for illustration. However, the sensor-event combinations are too numerous to show separately as they add up to over two million combinations: 1000 sensors responding to 1000 leakages, 1000 valve mutations, and 7 supply changes. Instead, the sensor responses are summarized in so-called *impact matrices*, where each matrix contains 1000 event x 1000 sensor combinations. The color coding reflects the exceedance of the deviating sensor signal above the detection limit. A white entry means “no detection”.

The impact matrix for pressure with a threshold of 0.5 MWC is characterized by a vertical “striping” pattern. This striping reflects a large variation in the fraction of sensors that are triggered by leakage events, from “no detections”(white matrix columns) to “detection by all sensors” (fully colored matrix columns). There is no obvious clustering in the vertical direction. This means that positive detections are not specific to certain locations in the distribution network. Indeed, a non-preferential distribution is expected for leakage events and sensor locations that are both randomly distributed over the network.

The pressure impact matrix to valve mutations (detection threshold 0.5 MWC) is shown in Figure 8. Similar to the leakage impact matrix , the number of sensor detections varies between events but it is much sparser for valve events than for leakages (cf. Figure 7 and Figure 8). This is attributed to valve closings that generally cause a pressure disturbance of smaller extent than the leakage that are modeled as a full pipe break in this study.

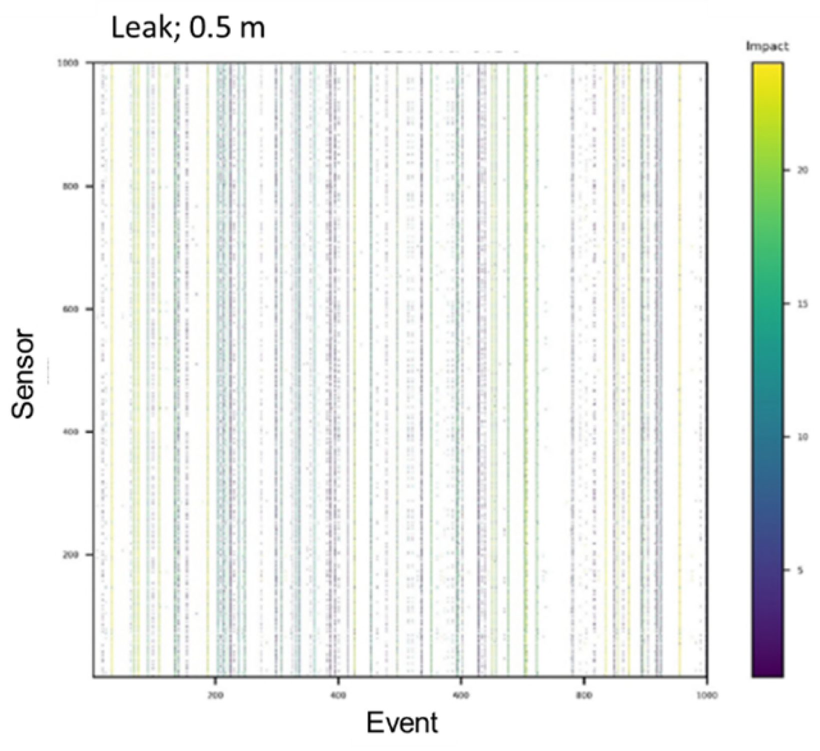


Figure 7. Pressure impact matrix (to leakage events) calculated with a sensor detection limit of 0.5 MWC.

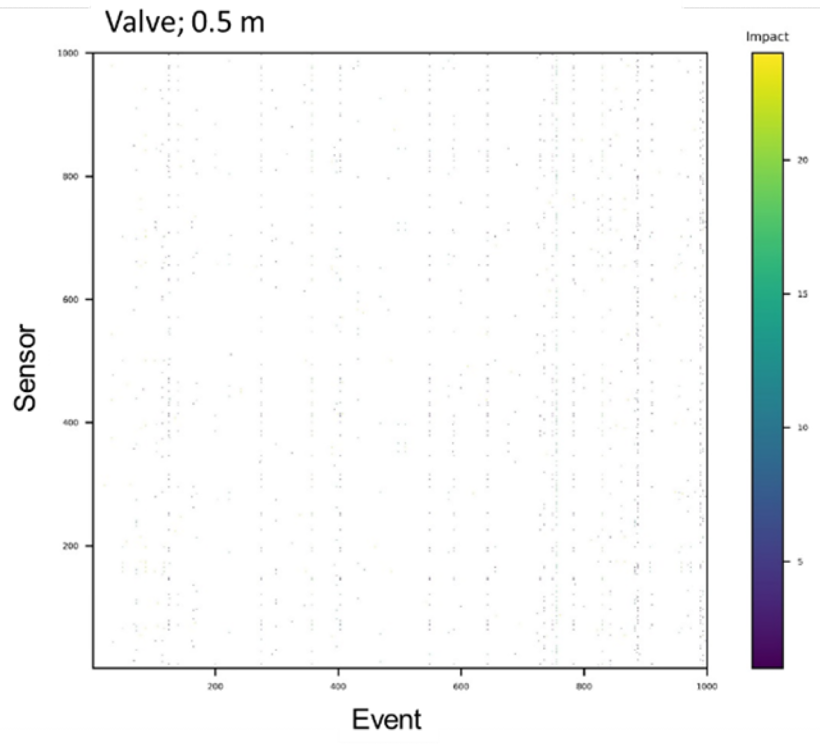


Figure 8. Same as Figure 7 but for valve events.

The pressure impact matrix for supply anomalies (Figure 9) has only 8 columns, reflecting the number of events scenarios. At a detection limit of 0.5 MWC, small supply anomalies (10% and 20% variations, either positive or negative) are not detected, but supply anomalies of 30% or larger induce detectable pressure variations (matrix columns to the left and right). The weak pressure sensitivity to supply is a result from the pressure control of the main supply (P.S. De Punt) that will compensate for any change in the support supply (Ruisscherbrug). Although this induces a change in the zonation of water types, the effect on the system pressure is limited. This is true for both the model and the real network, although some care has to be taken in the interpretation of the results because the pressure control in the model (prescribed at P.S. De Punt) differs from that in the real distribution network[1].

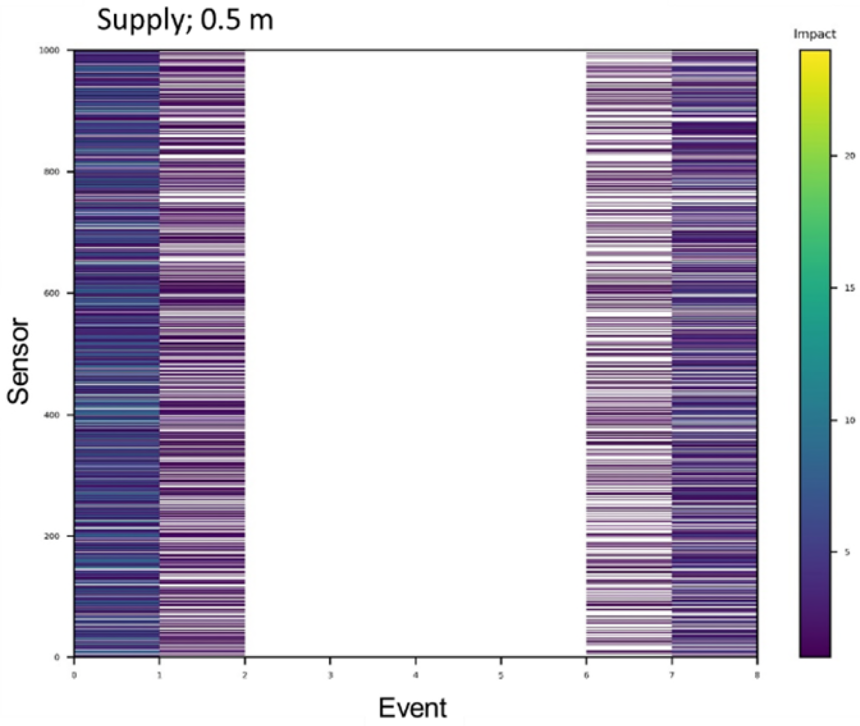


Figure 9. Same as Figure 7 but for supply anomalies. The 8 matrix columns correspond to supply from Ruisscherbrug of -40%, -30%, -20%, -10%, +10%, +20%, +30%, and +40-% relative to the reference model.

3.2.2 EC-response to leakages, valves mutations, and supply proportion

The impact matrix is denser for the 10 µS/cm than for the 50 µS/cm threshold, which reflects that leakages are easier to detect at a lower detection threshold, as expected. In contrast to the vertically-striped pressure impact matrix (Figure 7), the EC matrix shows a cross-striped pattern with both horizontal *and* vertical stripes – indicating a location-preference of the leakage events. A likely explanation is that in the mixing zone leakages can trigger a detectable EC-response , while many sensors outside the mixing zone will never experience a change in EC because they remain in the same supply zone no matter what happens in the network. EC is more sensitive at the chosen thresholds than pressure is, as reflected by the EC impact matrices of 10 and 50 µS/cm that are “denser” than the pressure impact matrix (of 0.5 MWC).

[1] For example, if in the real network the support supply increases and causes a change in the system pressure at the monitor pressure gauges (that feed back to the main supply De Punt), then the main supply will start changing the system pressure in the opposite direction, thereby compensating the initial pressure change. In that case the (uncompensated) model calculation will overestimate the detectability of supply anomalies. Something similar happens in the model (in which De Punt would compensate a change in system pressure by adjusting the flow) but the control types are not identical.

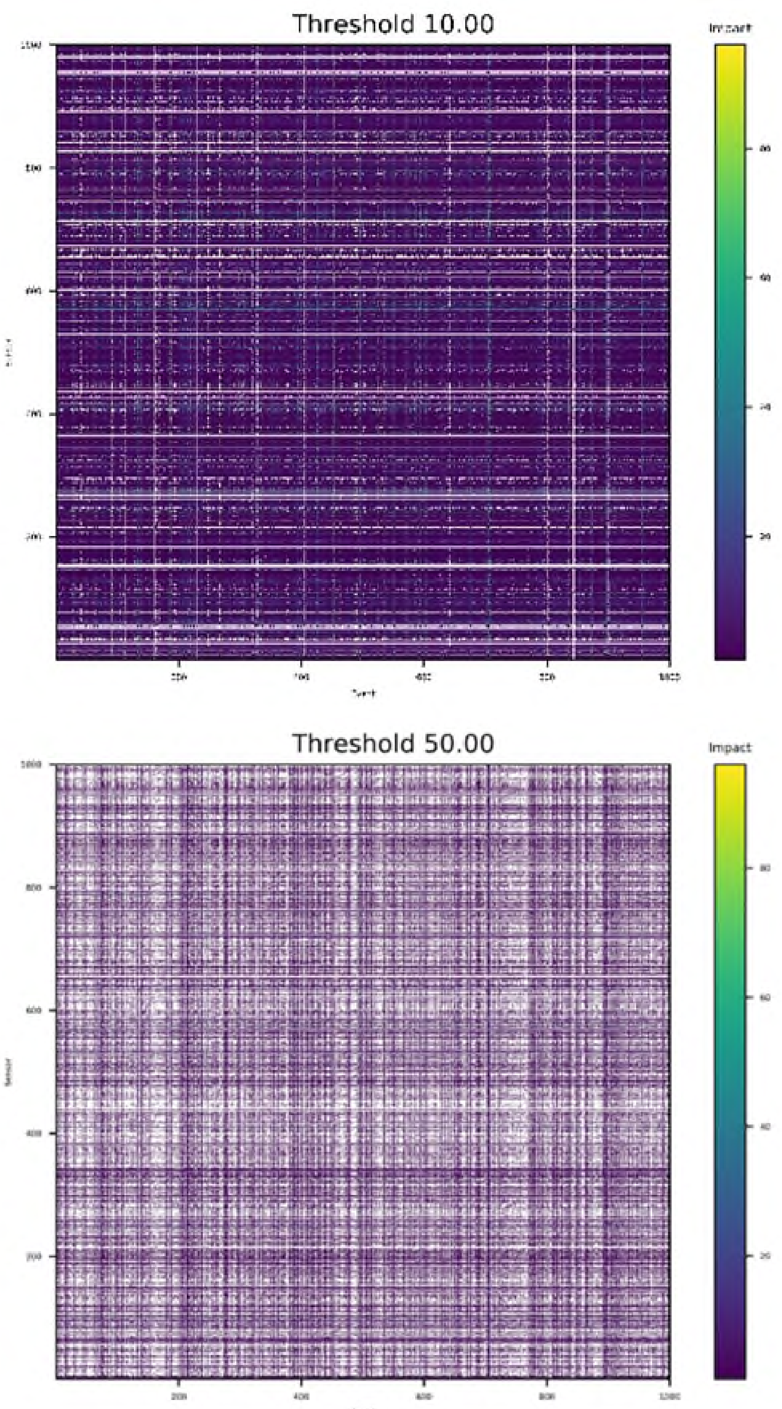


Figure 10. EC impact matrix for leakage events with a sensor detection limit of 10 mS/cm (top panel) and 50 mS/cm (bottom panel). The detection time is evaluated over the last day of a 4-day period, to allow for deviations in EC to spread with the water over the entire network, i.e. taking into account the maximum residence time of approximately 3 days.

The EC impact matrices corresponding to sensor mutations for detection limits of 10 and 50 µS/cm is shown in Figure 11. Compared to the EC response to leakages (Figure 10), the matrices are more sparsely populated. This reflects a higher detection likelihood for the modeled leakages than for valve mutations and this is in line with the trend for the pressure response (Section 3.2.1; Figure 7 and Figure 8).

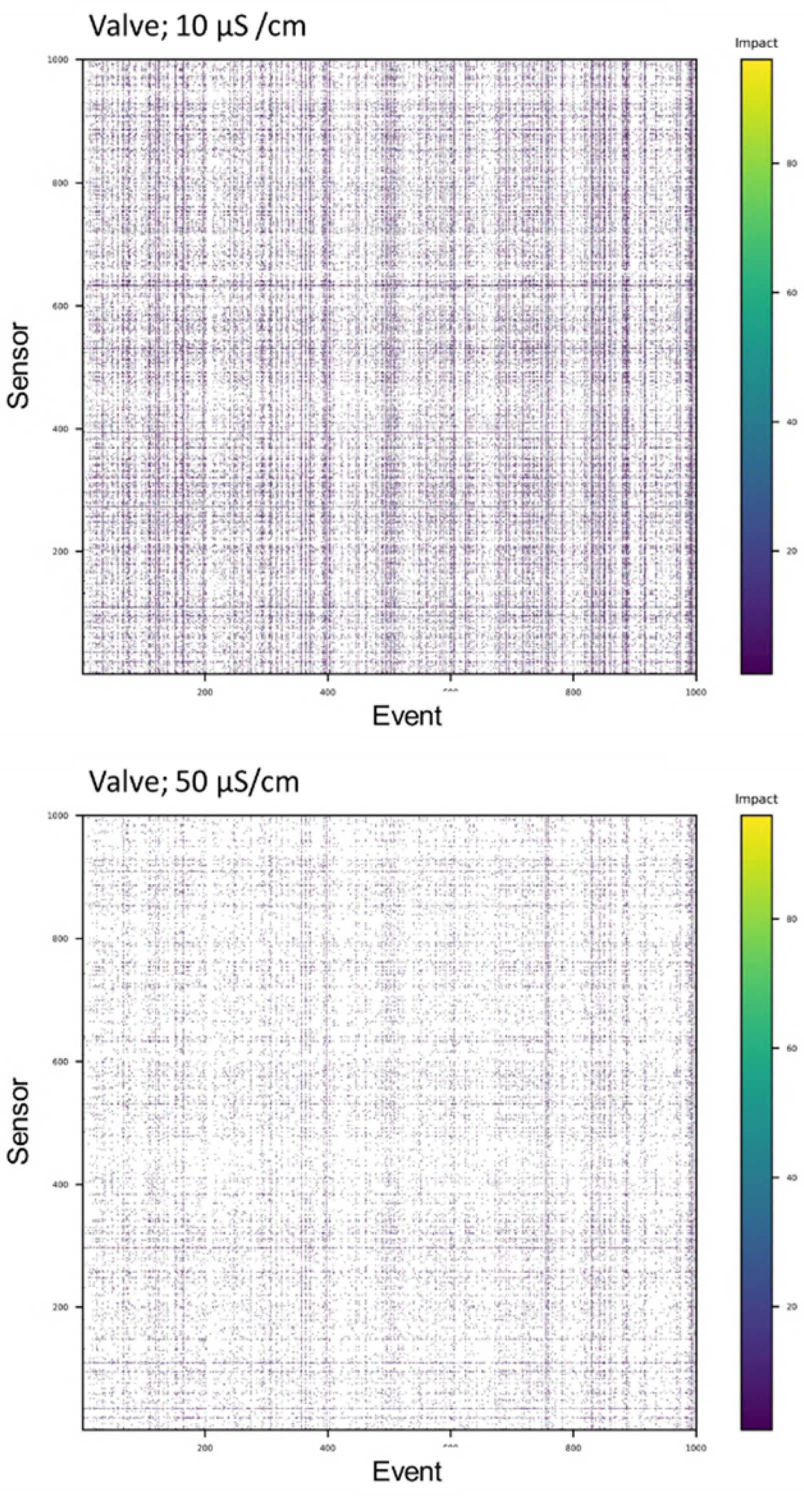


Figure 11. Same as Figure 7Figure 10 but for valve events.

The EC impact matrices to supply events (Figure 12) show that the detectability increases with event size and decreases with detection threshold, in line with the above-mentioned results for pressure (Figure 9 and Figure 12). In contrast to the pressure, even a small (10%) anomaly in the supply proportion is detectable in EC. This is understood as nodes switching from one source to the other will experience a large change in EC not matter what the magnitude of the driver was.

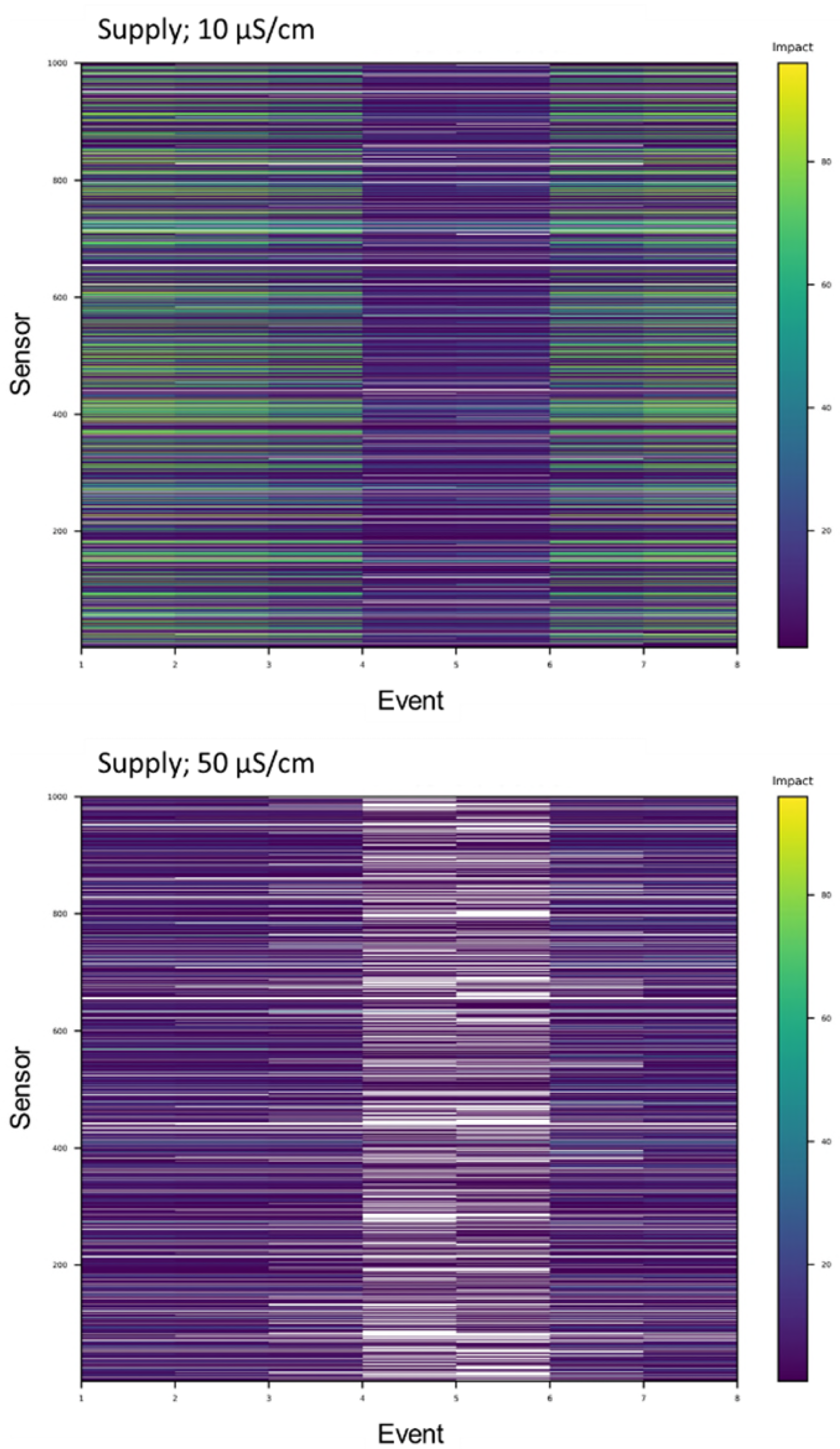


Figure 12. Same as Figure 7Figure 10 but for supply anomalies.

3.3 Detection limit and sensor placement

3.3.1 Spatiality of detection likelihood

Building upon the results described above, a more extensive investigation focused on:

i. the influence of the pressure sensor detection threshold on the detection likelihood to leakage and valve events;

ii. the recommendation of 15 pressure sensor locations optimized for event detection (in addition to 7 currently installed combined pressure and EC meters).

To this end, the pressure impact matrices were calculated for a range of detection limits (0.1, 0.3, and 0.5 MWC respectively). In order to improve the accuracy of calculated detection likelihoods, the number of potential sensor locations was maximized to all (25,000+) network nodes in the 100 – 300 mm diameter range, instead of only 1000 locations in the previous calculations. The calculations were limited to leakage and valve events because the previous modeling results showed that the pressure is relatively insensitive to supply anomalies, i.e. no events detected below a 20% anomaly in supply volume at the support supply Ruisscherbrug.

Insight into the spatial distribution of event detection likelihood over the network is provided by the maps in Figure 14. These maps show the ability of a single sensor to detect a single event that may occur anywhere I the network. Consistent with (and in extension to) earlier results (Section 3.2.1), the likelihood is higher for leakages than for valve events and decreases with the detection threshold. The results show that the detection likelihood of pressure sensors varies across the network, but is relatively uniform within the spatial extent of neighborhoods. The highest detection likelihoods occur in the northern part of the network. Possible explanations are:

- event-induced pressure changes are more easily compensated by the pressure-controlled supply in the South (De Punt) than in more distant areas;

- a higher pipe density in and around the city center of Groningen (in the North of the DWDS) increases the chance of an event to occur in close proximity to the sensor.

The spatial pattern of detection likelihoods varies between calculations of different sensor detection threshold. A viable explanation is that the detection threshold “filters” the events: leakage magnitudes depend on pipe diameters (Figure 4) and, because pipe diameters (and hence leakages) are distributed unevenly over neighborhoods, this can cause a threshold-specific spatial response pattern.

This study did not define an a priori target on the level of detection likelihood that would be acceptable or of practical use. A leakage detection likelihood of up to 36% (for leakages) or 19% (for leakages and valves) using a 0.1 MWC threshold (Figure 14) seems, arguably, a reasonable performance for practical purposes. However, increasing the threshold to 0.5 MWC decreases the likelihood to only 8% and 4%, respectively. This demonstrates that not every *measurable* events will also be *detectable*: some events will remain ‘below the radar’ because the signals they induce are too weak in comparison to noise levels of a real-life distribution system.

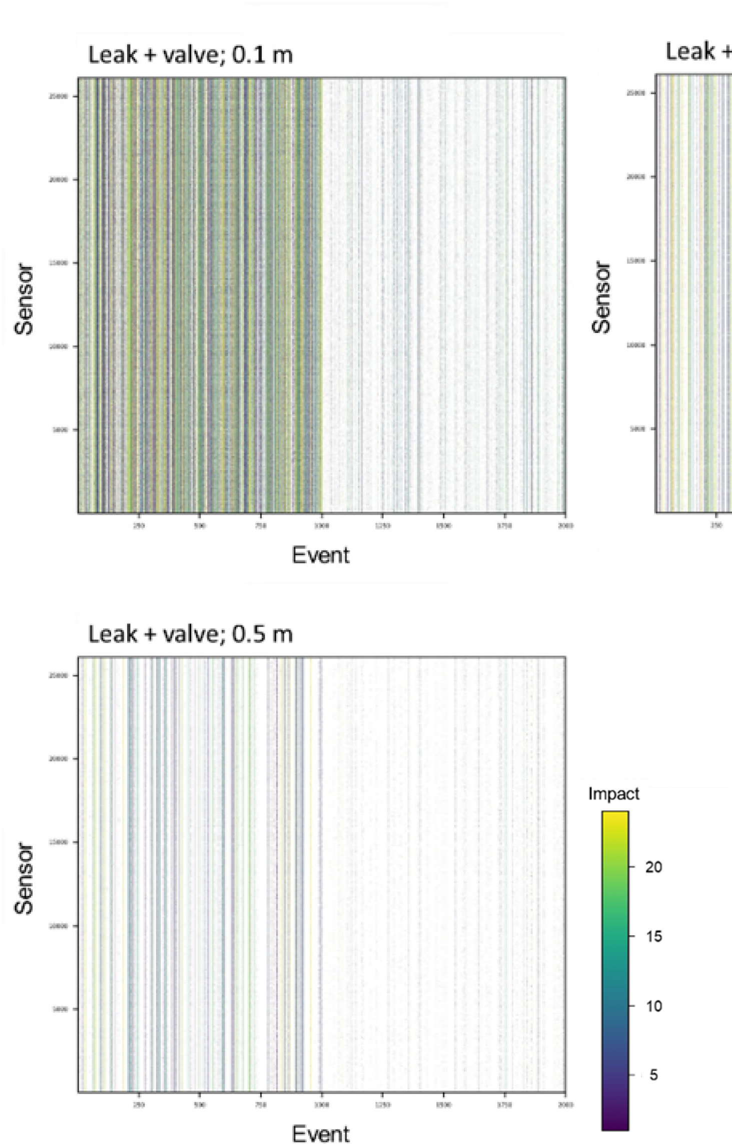


Figure 13. Impact matrices for pressure response for a sensor detection limit of 0.1, 0.3 and 0.5 MWC (as indicated by the labels). The response to leakages and valve mutations are shown in the left- and right-hand side of each matrix, respectively.

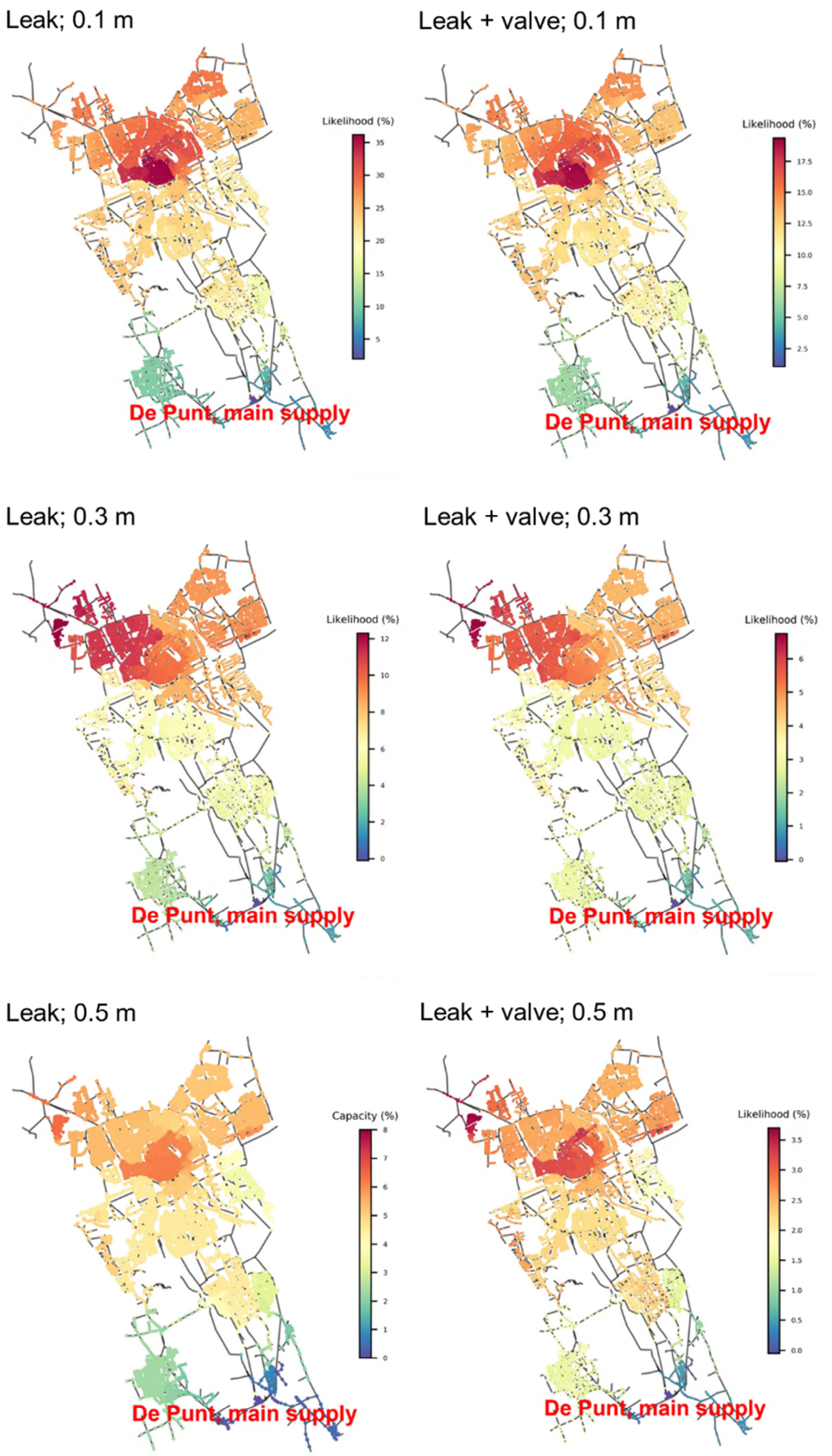


Figure 14. Likelihood of event detection with pressure sensors. From left to right, the detection limit changes from 0.1 to 0.3 to 0.5 MWC as indicated by the labels. The panels on the left depict the responses to leakages; those on the right response to leakages + valve mutations.

3.3.2 Influence of sensor networks size on detection likelihood

The sensor network detection likelihoods were calculated for the event types ‘leak’, ‘valve’ and ‘leak + valve’ . In these calculations, the sensors were distributed randomly over the network. The corresponding results for detection thresholds 0.1, 0.3, and 0.5 MWC and are shown in Figure 15. Each result is shown both for *all* sensor locations as well as zoomed in to the first 30 sensor locations only. Vertical bars reflect the spread of 1000 outcomes with random sensor placements and, hence, demonstrate the influence of the randomization.

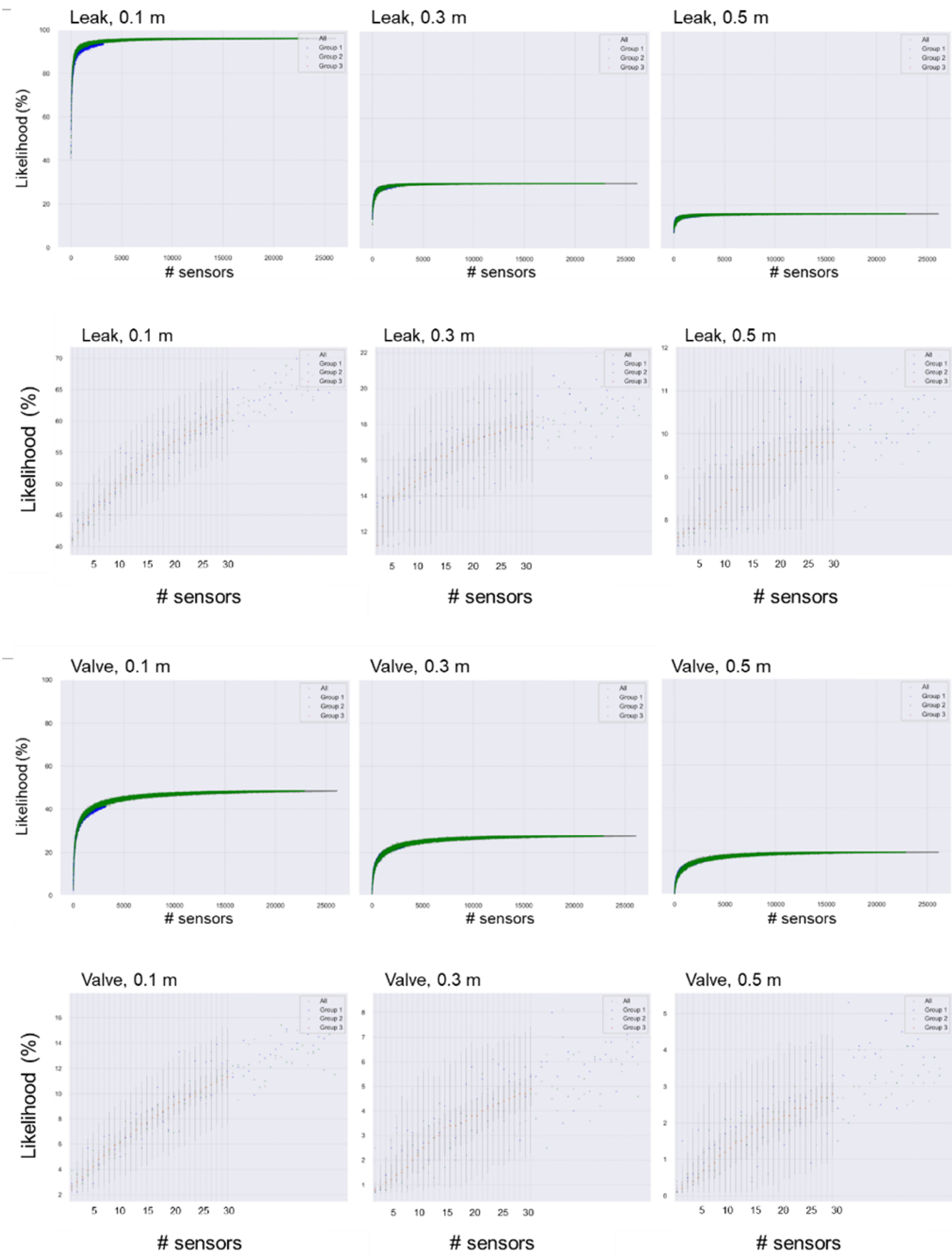
As before, the detection likelihood (i) decreases with increasing threshold and (ii) is higher for leakages than for valve closings with the values of “valve + leaks” approximately in between the two end members. In addition, the results show the influence of:

- *Sensor number*

  The detection likelihood increases with the number of sensors. The initial increase is very sharp (30 sensors already cover approximately 2/3rd of the maximum likelihood that would be achieved with 1000s of sensors in the network), and gradually levels off. Thus, the added value decreases with the installation of subsequent sensors.

- *Sensor location*

  The detection likelihood increases somewhat “irregularly” with the number of sensors, creating a “cloud” of data points rather than a thin curve. This is attributed to the location-specificity of the detection likelihood for a set of randomly placed sensors. This location-specificity is further demonstrated by the calculated likelihoods of 1000 sensor randomizations (at the same sensor number), shown by the vertical bars (for sensor numbers below $n \leq 30$ in Figure 15). These results demonstrate the profound implications of proper sensor placement. For example, for $n=15$, the effect of changing the randomization from average to maximum likelihood is roughly similar to doubling the number of sensors from 15 to 30 (both with an average likelihood).


Leak, 0.1 m
Leak, 0.3 m
Leak, 0.5 m
Likelihood (%)
sensors
All
Group 1
Group 2
Group 3
Leak, 0.1 m
Leak, 0.3 m
Leak, 0.5 m
Likelihood (%)
sensors
Valve, 0.1 m
Valve, 0.3 m
Valve, 0.5 m
Likelihood (%)
sensors
Valve, 0.1 m
Valve, 0.3 m
Valve, 0.5 m
Likelihood (%)
sensors

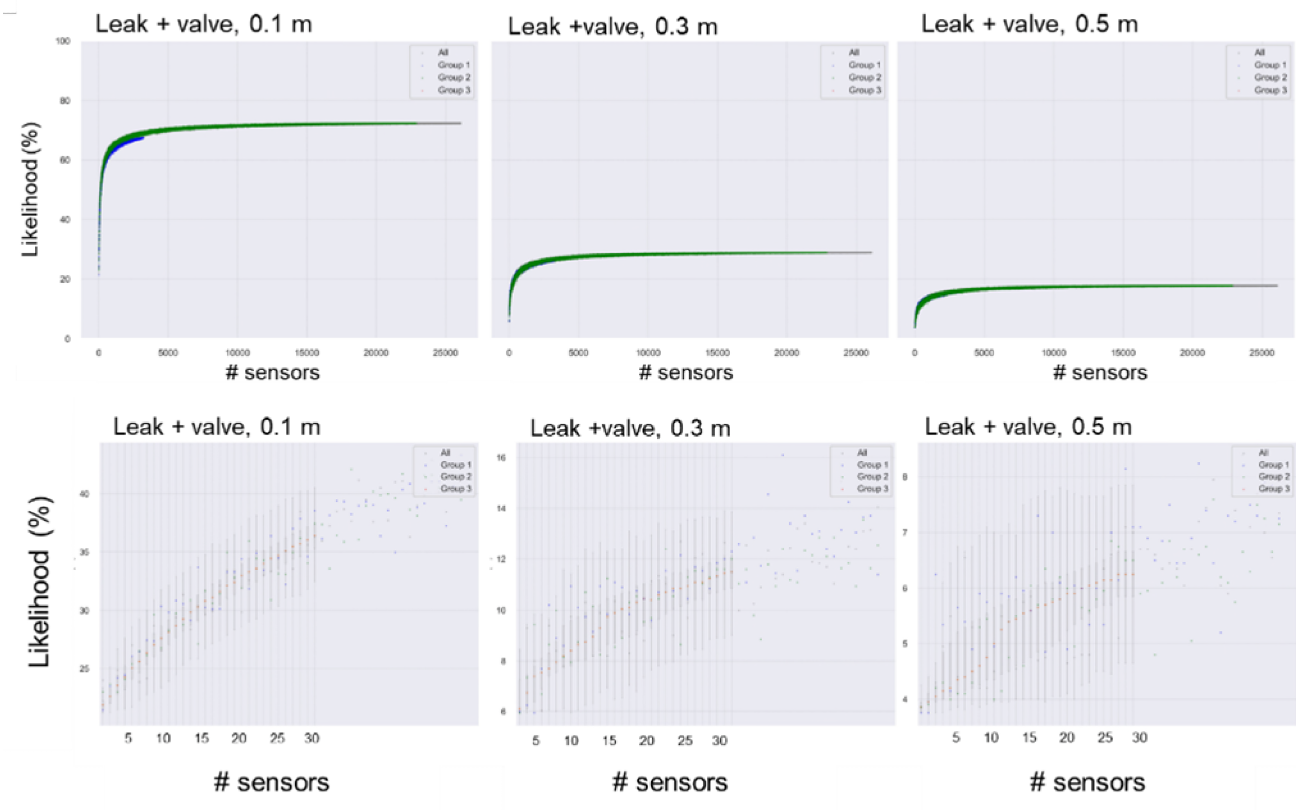


Figure 15. Sensor network event detection likelihoods as a function of the number of sensors. Event types (leak, valve, leak + valve) and sensor detection threshold values are indicated above each panel. Every panel is shown twice: for all network nodes and zoomed in on the first 30 sensors. The colors refer to the pipe diameter of the sensor location: Group 1: all sensors placed on <100 mm diameter pipes; Group 2: one or more sensors are placed on 100 -300 mm diameter pipes; Group 3: all sensors are placed on >300 mm diameter pipes.

3.4 Optimizing the locations of 15 pressure loggers

Next, the locations optimized for maximum detection likelihood were calculated for 15 pressure loggers in addition to 7 existing sensors that measure pressure and EC.). The choice for the number of 15 sensors was established in coordination with WBG as a compromise between an increase of the detection likelihood provided by the sensors (see Figure 15) and the investment in purchasing and installing the sensors by WBG.

The optimized sensor locations were calculated for nine combinations of different threshold values (0.1, 0.3, and 0.5 MWC) and three different event types (‘leakage’, ‘valve’, and ‘leakage + valve’), shown in Figure 16. For a small (0.1 m) detection threshold, more sensors are located in the city center of Groningen than for subsequently larger thresholds (0.3 and 0.5 m). A possible explanation is that the city center contains mostly small diameter pipes associated with small leak and valve events that are easily detected, provided the detection threshold is low. In contrast, at larger detection thresholds only the bigger events can be detected that are more typical for larger pipes in the periphery of the city. Hence the optimized sensors are placed in a more “decentralized” spatial pattern.

A more nuanced difference is visible in the sensor locations when comparing the result for pressure events on the one hand with those of valve events or leakages and valve combined on the other hand. When valves are included, the optimal sensor locations are often at or close to the dead-ends of pipe branches. This is a plausible result, considered that a valve mutation affects the pressure in a manner that is more directional (meaning: downstream from the valve) than a leakage does. Thus dead-end pipe branches of the network are expected to be particularly sensitive to upstream valve mutations.

The nine solutions are all mathematically valid. Only a few of the sensors appear at the exact same location in multiple solutions and some are approximate. Despite few exact matches, the solutions show a similarity in the sense that their spread across the network is to a high degree homogenous: there are no obvious spatial concentrations in specific sub-regions of the network. This might indicate that a sensor configuration optimized for one purpose performs reasonably well for another, but this suggestion has not been verified. The experts from Waterbedrijf Groningen informed KWR that their choice was the combination of a 0.1 MWC threshold and the ‘leakage + valve’ event scenario.

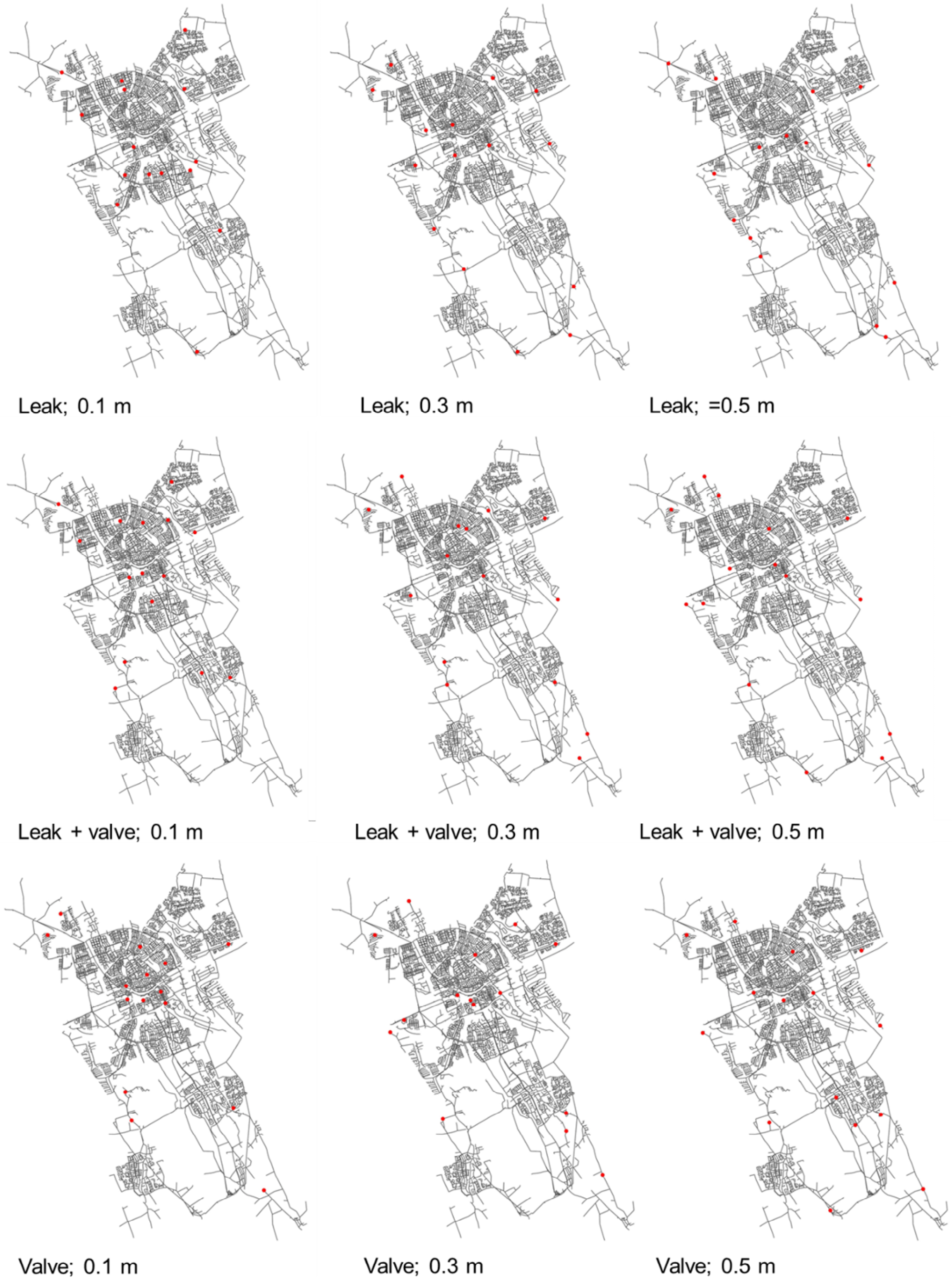


Figure 16. Optimized sensor network locations for 15 pressure loggers to be installed in addition to 7 combined sensors (pressure + EC). The titles below each panel indicate the event type ('leak', 'valve', 'leak + valve') and the sensor detection threshold values.

4 Concluding remarks

4.1 Conclusions

This study investigated the likelihood of networks of pressure and electrical conductivity (EC) sensors in a DWDS model to detect (synthetic) operational events. To this end, hydraulic model simulations of the city of Groningen were used. The detection of events was calculated based on the offset of sensor signals calculated from event scenarios to those of a scenario of standard operation.

The main findings of this first part of the network analysis (Section 3.2) are:

1. Leakages (modeled as full pipe breaks in this study) are substantially more likely to be detected than valve closings (using the same set of 1000 potential sensor locations). This was demonstrated in a qualitative way (by visual comparison of the impact matrices) for both pressure and EC sensors.

2. Modeled anomalies in the supply volume proportion between two supply locations are more readily detected by EC than by pressure sensors (in the set-ups that were investigated). At least one of the 1000 randomly-placed EC sensors (detection threshold of 10 or 50 µS/cm) detected a supply anomaly larger than 10% (the smallest anomaly tested), whereas pressure sensors (threshold of 0.5 MWC) detected only anomalies of 30% or larger.

3. Compared to pressure sensors, the EC sensors show a stronger dependence on their *location* within the DWDS model (with regards to detecting leakage and valve events). This is qualitatively demonstrated by the cross-striped patterns of the impact matrices.

Both effects (2) and (3) are attributed to (synthetic) event-induced disruptions of the mixing zone in the Groningen network model that will affect EC sensor signatures but leaves the system pressure largely unaffected.

The main findings of the second part (Section 3.3 and 3.4) are:

4. For subsequently higher sensor detection thresholds (0.1; 0.3; 0.5 MWC,) the calculated maximum detection likelihood of pressure sensors decreased in response to synthetic leakages (from 36% to 12% to 8%) and valve mutations (19% to 7% to 4%). The absolute likelihood values vary across different neighborhoods, but the relative dependence on the detection threshold is roughly similar to the abovementioned percentages (Figure 14). A high threshold is undesirable as it curbs the performance, but necessary to avoid an abundance of false positive event detections caused by stochastic noise levels and other signal noise expected for a real-life network.

5. The calculated spatial pattern of detection likelihoods varies across the Groningen network model, with higher likelihoods occurring in the Northern area (Section 3.3.1, Figure 14). Possible explanations for this area dependence are that (i) event-induced pressure anomalies are less readily compensated at a large distance from the pressure-controlled supply in the South and/or (ii) the denser network structure in the city center fosters the occurrence of more events. Furthermore, the spatial pattern of detection likelihoods varies slightly (on the level of neighborhoods) between calculations of different sensor detection thresholds. This is attributed

to the threshold value filtering out events below a certain magnitude, in combination with a site-specific distribution of pipe diameters on which these event magnitudes depend.

6. Analysis of the event detection likelihood of pressure sensors in addition to seven installed combined sensors (EC and pressure) showed that:

    a. The additional increase in detection likelihood progressively reduces for subsequently larger numbers of installed pressure sensors. After a sharp initial increase, the added value levels off: the first 30 additional pressure sensors cover approximately 2/3rd of the maximum likelihood that would be achieved with 1000s of sensors in the network.

    b. A set of 1000 randomizations of sensor locations (at the same sensor number) is accompanied by a wide range of detection likelihoods. For the specific case of 15 additional pressure sensors, the increase from the *average* to the *maximum* likelihood is comparable to a doubling of the number of sensors. This clearly inllustrates the value of careful sensor placement using optimization.

7. Optimizing the location of 15 synthetic pressure sensors (in addition to seven installed pressure and EC sensors) demonstrated the range of sensor network configurations as a function of (i) the applied sensor detection threshold and (ii) the optimization criterion (detecting leakages, valve mutations, or both). This provides a “menu” of viable solutions for extending the existing sensor network. The water utility can choose from this menu, depending on their valuation of the objective.

    a. For a small detection threshold (0.1 MWC), more sensors are located in the city center of Groningen than for subsequently larger thresholds (0.3 and 0.5 MWC) in which the sensors are placed in a more “decentralized” spatial pattern. A possible explanation is that the city center contains mostly small diameter pipes associated with small leakage and valve events that are easily detected, provided the detection threshold is low.

    b. When the optimization criterion involves maximizing valve event detection (solely, or in addition to leakage detection), the optimal sensor locations are closer to the network extremities, i.e. at or near the dead-ends of pipe branches. This outcome is plausible, because the pressure effect of valve settings is more directional in nature than that of leakages: in other words, the results suggest that the dead-end locations are particularly sensitive to upstream valve mutations.

4.2 Reflection of water utilities on this research with regards to implementation

Water companies are increasingly focusing on realizing so-called smart water networks (SWN). By placing sensors in the distribution network, information can be obtained to improve operations and enhance asset management. Consider, for example, the rapid detection of leaks, deviations in water flows and valves that are in the wrong setting. When placing sensors, a proper balance is sought between costs, benefits and manageable data flows. For this purpose, it is important to obtain as much information as possible with the least number of sensors. The methodology developed by KWR for optimizing sensor locations helps with this. The methodology provides insight into the relation between the employed number of sensors, the coverage and the detection likelihood for different configurations of sensor locations. This research helped Water Company Groningen determine suitable sensor locations in the city of Groningen. Because customized results were delivered for the placement of 15 additional sensors in the city, the results are immediately implementable. For use in projects other than the city of Groningen, it is desired that the scripts used by KWR are made available to Waterbedrijf Groningen and the other water companies so that they can implement them themselves.

4.3 Recommendation for implementation and future research

The main recommendation of this study is to apply and test the method in practice. As a first step it is advised to install 15 pressure sensors in addition to the seven previously installed pressure and EC sensors in the real-life Groningen pilot area at the optimized sensor locations (Section 3.4). Subsequently, the event detection performance of the augmented sensor network should be tested in the context of a real-life distribution system. This will likely involve challenges such as dealing with the presence of signal noise and imperfect data quality. For testing purpose, the event detection method proposed in this study can be followed. The method would still require practical adjustments (such as reading in data in a specific data format) as well as conceptual ones (such as deciding on a useful reference scenario and adjusting sensor detection thresholds to the actual system noise). It is advised to conduct anomaly scenarios in the real-life network that mimic the event detection in this study, including leakage events (simulated by increased water demand), valve closures, and supply anomalies (temporarily changing the partitioning of supply volumes between Ruisscherbrug and De Punt). Setting up the test cases involves selecting suitable leakage and valve event locations and these can be determined using the network analysis method devised in this study[2]. The results of these practical tests can then be used in a comparative analysis to the theoretical results presented in this report. This will shed light on how the detection likelihood varies with the number of sensors, the sensor detection threshold, or with the event anomaly magnitude.

Based on the results of this study, detection threshold ranges recommended for practical application in Groningen are 0.1 to 0.5 MWC for pressure and 10 to 50 µS/cm for EC. These values are expected to give a reasonable compromise between avoiding false positive detections (because of e.g. stochastic noise) and avoiding false negative detections (because of true event signals that remain below the threshold). This is inferred from sensor measurements in the real-life network, albeit for a specific evaluation period. A more detailed network analysis can improve the insight into appropriate threshold values, for example by including stochastic demand variations in the models or applying representative noise to the sensor signals. This would allow for a (theoretical) performance evaluation including an analysis of true/false positive/negative detections. Furthermore, instead of the uniform EC-threshold used in this study, one could consider a threshold that varies in space and time, based on EC-variations of the reference scenario. In contrast to pressure, EC-fluctuations can show variations that are strong in some regions (commuting mixing zones for example) and weak in others (for example regions that receive water with a stable EC from a single supply). A challenge will be to find an optimum level of temporal and spatial granulation to avoid overfitting (unpredictable EC-variations could result in undesired false positive detections in case the granulation is chosen too fine).

[2] The impact matrices serve as a look-up table of sensitivity of the 22 sensor locations to leakages (albeit of a single fixed size), valve closures and supply anomalies. However, this was only done for the full set of network nodes for pressure, not EC, so additional calculations may be needed to calculate event locations that trigger useful sensor signals.

5 Literature

Berry, J., Hart, W. E., Phillips, C. E., Uber, J. G. & Watson, J.-P. (2006). “Sensor placement in municipal water networks with temporal integer programming models”. J. Water Resources Planning and Management, 132(4), 218-224.

Crowl, D.A. & Louvar, J.F. (2011). “Chemical Process Safety: Fundamentals with Applications, 3 edition”. Upper Saddle River, NJ: Prentice Hall, 720p.

Cristofides, N (1975). “Graph Theory. An Algorithm Approach”. New York: Academic Press.

Hansen, P. & Jaumard, B (1997). “Cluster Analysis and Mathematical Programming”. Mathematical Programming 79, p. 191-215.

Klise, K.A., Murray, R. Haxton, T. (2018). “An overview of the Water Network Tool for Resilience (WNTR)”. In. Proceedings of the 1st International WDSA.CCWI Joint Conference, Kinston, Ontario, Canada, July 23-25, 075, 8p.

Klise, K.A., Nicholson, B.L. & Laird, C. D. (2017) “Sensor placement optimization using Chama”. United States: N. p., 2017. Doi: 10.2172/1405271.

Krarup, J. & Pruzan, P (1983). “The simple plant location problem: survey and synthesis”. European J. Oper. Res. 12, N 1, p.36-81.

Legg, S.W., Benavides-Serrano, A.J., Siirola, J.D., Watson, J.P., Davis, S.G., Bratteteig, A. & Laird, C.D. (2012). “A Stochastic Programming Approach for Gas Detector Placement Using CFD-Based Dispersion Simulations”. Computers & Chemical Engineering, Volume 47, Pages 194-201.

Resende M., Werneck R. (2004). “A Hybrid Heuristic for the p-Median Problem”. Journal of Heuristics, 10(1):59-88.

USEPA12, United States Environmental Protection Agency. (2012). “TEVA-SPOT Toolkit User Manual”. U. S. Environmental Protection Agency Technical Report, EPA/600/R-08/041B.

USEPA15, United States Environmental Protection Agency. (2015). “Water Security Toolkit User Manual”. U. S. Environmental Protection Agency Technical Report, EPA/600/R-14/338, 187p.

Van Summeren, J. (2016). “Investeringen en rendementen van sensornetwerken ten behoeve van waterkwaliteitsbewaking - TKI INTEREST”. Report KWR 2016.052, KWR Watercycle Research Institute, Nieuwegein, Netherlands.

Van Summeren, J. & Castro Gama, M. (2020). “Smart Water Networks -Pilot Groningen”. BTO 2021.202(s). KWR Water Research Institute, Nieuwegein, Netherlands.

Van Summeren, J. & Hillebrand, B. (2019). “Verkenning van identificatie van afsluiterstanden in het distributienet van Groningen”. BTO 2019.029. KWR Water Research Institute, Nieuwegein, Netherlands.

Van Thienen, P. (2014). “Strategieën voor optimale plaatskeuze van waterkwaliteitssensoren in het distributienet”. KWR Watercycle Research Institute. BTO 2014.046.

Vonk, E. & Vries, D. (2016). “Datamining voor assetmanagement –inventarisatie en voorbeelden uit de watersector”, BTO 2016.007, KWR Watercycle Research Institute, Nieuwegein, Netherlands.

Vries, D. & Van Summeren, J. (2017). “Valve status verification and sensor error detection via causal inference from sensor data”. Computational and Control for the Water Industry (CCWI) conference 2017, Sheffield, U.K. Proceeding F94.