Leakage localization in water distribution system using heuristic method

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Abstract

Data-driven leakage detection and localization in Water Distribution Networks (WDN) is a challenging task. In this paper, the Leak Localization by Distance (LLD) heuristic algorithm is proposed, which considers limitations existing in practice: it only uses the measurement data, and a network simulator is unnecessary. The proposed method is tested in simulation on two leak scenarios.

1 Introduction

The problem of detecting and locating leakages in a water distribution system is gaining in recent days more and more economical and even strategic importance. Water leaks in water distribution systems account for up to 27% of the total amount of water extracted [1]. The economic losses are therefore very high. In addition, there is a risk of contamination of the water with bacteria and a threat to the health of drinking water recipients. However, the most important is the strategic dimension related to the security of society's water supply, with a constantly growing population and increasing water scarcity.

Methods that require the participation of operators and specialized equipment have been used for a long time to detect water leaks. This group includes: auscultation of the network with the use of a stethoscope, the use of acoustic loggers, hydrophones, ground-penetrating radar (GPR), floating leak detection system, gas injection methods, and tests with the use of an in-line inspection device [2; 3]. These methods allow the most accurate identification of the leak location, but the time needed to locate the failure is very long, which results in significant water losses. Moreover, the costs of such studies with specialized teams are high. They are often carried out at night, mainly due to the most negligible influence of acoustic disturbances.

The disadvantages mentioned above resulted in the development of WDN (Water Distribution Networks) monitoring systems, especially automatic detection and location of water leaks. Such a solution requires a permanent installation of appropriate metering for the water supply network. Diagnostic activities aim to obtain early detection capability and usually only rough fault localization. A coarse location, e.g., indicating a network node, close to which a leak has arisen, significantly narrows the area to look for failures using the methods with the participation of staff, discussed above.

The number of possible places for leakage is endless. Therefore, to simplify the problem, it is assumed that the leaks occur at the network's nodes. The number of possible leak sites remains vast, but it is finite. It is permissible for practical reasons to bring the leakage point closer to the network node.

The difficulties in locating leaks result from the inability to obtain accurate network models and insufficient metering of the water distribution network. The network model is defined by a set of highly coupled nonlinear equations without an unambiguous solution [4; 5]. The network simulators used, mainly based on the EPANET package, require calibration. The calibration results represent the state of the system only in a short time due to the non-stationarity of the water supply network. Water consumption in the water supply system changes mainly in the daily, weekly, and seasonal cycles. Moreover, the water supply network is subject to constant changes related to the technical condition of devices, expansion, and modernization. Thus, it can be concluded that the water supply network is a highly non-stationary facility undergoing constant changes.

An accurate measurement system is essential for the functioning of any diagnostic system. Water distribution systems mainly use pressure measurements at various points in the network and flow measurements at points supplying individual DMA (District Metered Area) zones and at points of water intake by large wholesale customers. A common problem is an insufficient number of measuring devices installed in water networks. Recently, it has been systematically increased, but the number of measurement data is still insufficient for the needs of automatic diagnostic.

The heuristic leak detection method **Localization by Distance (LLD)** proposed in this paper considers the limitations existing in practice to ensure the possibility of a simple application. It only uses the existing measurement data. A network simulator is not necessary. There is also no need to know the sensitivity of residuals to leaks. The method can be used in separate DMA zones and in networks where division into zones is not used.

The paper is structured as follows: Section 2 introduces the problem of leak location and known approaches, in Section 3, the LLD algorithm for leak localization is introduced. Section 4 describes the model used for residual generation. In Section 5 results of numerical experiments using WDN simulators are described, and Section 6 concludes the paper.

2 Approaches applied to automatic leak location

There are two types of methods and the corresponding measuring devices used for network diagnostics. One solution is acoustic methods and measurements [3]. The second is using mathematical models and flows and pressures measurements in the water supply network. This paper will consider only the latter approach.

One of the easiest ways to detect and roughly locate leaks is to balance the water sold and pumped into the network. This method consists of dividing the network into zones and sub-areas. The amount of injected water, the amount of water discharged, and the consumption by consumers is measured. The difference between the volume of water injected into the network and the volume of water consumed by consumers is a measure of the size of the leakage/leakages. The water balance is charged with many errors. However, the regular balancing allows to detect emerging anomalies and roughly estimate the size of the leak while locating the leak with accuracy to a given zone.

The basic concept of real-time leakage diagnostics in water networks compares data from metering devices with data generated by a well-calibrated, up-to-date hydraulic network model in a leak-free condition. By analyzing the difference between the two datasets, unusual events can be detected, such as lesions [4; 5; 6]. The above method is based primarily on pressure measurements, which are much cheaper than flow measurements and are easy to install and maintain.

The papers [4; 5; 7] propose a method based on pressure measurements and leakage sensitivity analysis. The proposed methodology is based on the study of the residuals (the difference between the measurements and their estimation) using a hydraulic network model. In the first two works, the classical binary approach was used to locate leaks, in which the problem was selecting thresholds when assessing the residues. The work [7] proposes improving the localization method using residual sensitivity analysis for fault detection. The methodology was implemented and tested in one DMA zone in Barcelona.

An alternative solution is to use models based on historical measurement data from pressure and/or flow sensors. Among the methods for leakages diagnosing in distribution networks, based on the exploration of measurement data, one can distinguish methods using artificial intelligence models and statistical methods. Neural networks are widely used. They are used for modelling flows [8] and pressures, for detection [9; 10] and leak localization [11], forecasting the demand for water [12], water quality monitoring, [13] and contamination detection [14]. Fuzzy and neural-fuzzy models are also used [15; 8]. SVM (Support Vector Machines) models are also used to predict the inflow to the network and compare it with the actual inflow [8] and for localization of leakages [16].

Among the statistical methods for detecting anomalies, the most frequently used method is PCA (Principal Component Analysis) and its derivatives [17]. There are also used: linear discriminant analysis (LDA), Gaussian Process Regression (GPR) [18], and data-driven classifiers [19; 6].

In addition, there are reports on applications of Bayesian models [20; 21] and the Fourier series [22] for leakage diagnostics.

3 Leak Localization by Distance (LLD)

This paper proposes a heuristic leakage localization method called Leak Localization by Distance (LLD).

The method was developed under the following assumptions:

1. Topology of a water distribution network is known, in particular the distances between nodes.
2. Leak detection consists of generating the residuals for measurement signals calculated as differences between the modelled value and the measured value.
3. Only pressure and flow measurements are used.
4. The leaks manifest themselves by the deviation of residuals from zero. The larger the leakage, the more residual values for this leakage deviate from zero, and the range of its detection increases.
5. For flows: the residual is calculated as the modelled value y_M minus the measured value y. Signs of the residuals in the presence of leaks should be negative.
6. For pressures: the residual is calculated as the measured value y minus the modelled value y_M. Signs of the residuals in the presence of leaks should be negative.
7. The opposite residual sign indicates a sensor fault or a modelling error (or can be caused by the action of control systems, confront results in Section 5.5).
8. The sensitivity of the calculated residuals to leakage decreases linearly with increasing distance from the node with a leak.
9. Single faults are assumed.

Standardisation of residuals values

The standardization of the residual activation values is applied using the function:

$$\theta_j = sgn(r_j)\frac{(r_j/\tau)^4}{1+(r_j/\tau)^4} \tag{1}$$

where: r_j residual value in node j, τ threshold value, $\theta_j \in [-1,+1]$ - standardised residual value.

Leakage localization algorithm

The motivation behind the algorithm is as follows: the localization algorithm is carried after the leak was detected, i.e., the residuals have large enough values. The leak node is probably localized near the nodes where the largest residuals occur, but it can be a node without a measurement (without a calculated residual value). Therefore we select for analysis the set R^* of a few largest residuals. Furthermore, we assume that the leak only affects nodes located not further than the analysis range L and that the effect of the leak on the residual value decreases with the distance to the leak node. We estimate analysis range L as the largest distance between two nodes with large residual values, i.e., the approximate radius of the part of the network that is visibly affected by the leak. The final leak possibility function W_{vn} for each network node is a sum of contributions from the largest residuals weighted by their distances to the considered node (shorter distance means more important contribution).

LLD algorithm consist of the following steps:

1. The computed residuals form the set:
$$R = r_j : j = 1, , J, \quad (2)$$
where J denotes the number of residuals. We assume that residuals are calculated for every measurement.
Residuals for all flow measurements are calculated according to:
$$r_j = y_M - y \quad (3)$$
and for all pressure measurements according to:
$$r_j = y - y_M, \quad (4)$$
where: y measurement value, y_M modelled value. This method of calculating the residual values leads to negative residual values in the case of leakage. A positive value may indicate sensor fault.
2. The residual values are standardized according to Eq. (1).
3. In the localization algorithm only the set of largest residuals is considered. A subset of residuals with the cardinality N ($N = 3 - 5$) with the largest values is determined:
$$R^* = \{r_j : j = 1, , N : \bigwedge_{r_j \in R^* \wedge r_i \notin R^*} |\theta_j| \geq |\theta_i|\}. \quad (5)$$
If there are residuals with the same value as the smallest residue in the set R^*, the set R^* is extended by these residuals.
4. The distances $\{l_{ik} : r_i \in R^*, r_k \in R^*\}$ between measurement nodes, in which the residuals from the set R^* are calculated, are determined. l_{ik} is the shortest path in the network between nodes v_i and v_k, where residuals r_i and r_k corresponds respectively to the difference of measurements and modelled values in nodes v_i and v_k.
5. The L parameter is calculated as the range of the network analysis being conducted:
$$L = K \max(\{l_{ik}\}), \quad (6)$$
where we assume that K is selected from the range: $K \in [1, 1 - 1, 5]$.
6. For each network node v_n, the value of the leakage possibility function is calculated according to:
$$W_{vn} = \Sigma_{j:r_j \in R^*} |\theta_j| \cdot y_j(l), \quad (7)$$
where $y_j(l)$ is a function of the distance l of a given network node v_n from the node where jth residual is computed:
$$y_j(l) = 1 - \frac{l}{L} \quad (8)$$
Then nodes of the network in the specified search area are covered with the calculated W_{vn} values indicating the possibility of a leak. The highest values of the W_{vn} function indicate the nodes where a leak is most likely (probable).

LLD properties

The proposed heuristic leakage localization method has the following properties:

- A network simulator is not required. If available, it can be used to determine residual thresholds.
- It is not necessary to know the sensitivity of residuals to faults.
- In the diagnosis phase, the method uses only data from the measurements.

4 Residual generation

For a residual generation, we use Holt Winter's model. It is one of the methods for predicting time series with a seasonal (periodic) component. It uses triple exponential smoothing and was proposed in [23; 24]. Exponential smoothing is a method calculating a weighted average of current and past samples (more recent signal values have greater weights than the older values). The weight values decrease exponentially. With triple smoothing, exponential smoothing is applied to the base value, trend, and seasonal component.

The values are calculated according to [25]:

Base value:
$$l(k) = \alpha(y(k) - s(k-S)) + (1-\alpha)(l(k-1) + b(k-1)) \quad (9)$$
Trend:
$$b(k) = \beta(l(k) - l(k-1)) + (1-\beta)b(k-1) \quad (10)$$
Seasonal component:
$$s(k) = \gamma(y(k) - l(k)) + (1-\gamma)s(k) \quad (11)$$
Smoothed value:
$$y_M(k) = l(k) + s(k-S), \quad (12)$$
where: l smoothed value of the variable, after elimination of seasonal changes, b rate of trend growth, k sample number, α, β, γ - smoothing coefficients, with values in range $(0, 1)$, values closer to 1 mean a greater weight of the current data, which results in better adaptation to the changes in conditions, but worsens the model's sensitivity to faults. Smoothing coefficients can be selected minimizing the mean square error for historical data; S season length (in the number of samples), in the experiments, we use signals with 10 minutes sampling time and weekly seasonality, which gives $S = 6 * 24 * 7$; y value of the measurement.

Initial values of trend and seasonal components should be estimated using historical data. Equations 9-11 describe additive version of the algorithm, alternatively multiplicative version can be used.

As a modelled value, we use smoothed measurement value.

Values of measured and modelled values in one of the network nodes (denoted J28) of the exemplary network (see description of the example in 5) are shown in Fig. 1. Red line indicates the start of the leak.

It should be noted that LLD does not assume any specific method for a residual generation. Therefore it is straightforward to apply with other modelling approaches.

5 Case study

5.1 WDN simulator

A hydraulic model of water distribution system is described, in general, by nonlinear algebraic equations. A mathematical description results from the first and second Kirchhoffs laws known from electrical engineering. The EPANET application uses computational methods to solve the equations of flow continuity and losses describing the hydraulic condition of the network in a given time interval. An equation is solved using the hybrid node-loop iterative method. Todini and Pilati [26], and later Salgado [27] called this method the Gradient Method. The Todini approach was used in the EPANET2 computing library. To simulate and evaluate diagnostic algorithms the WNTR python package

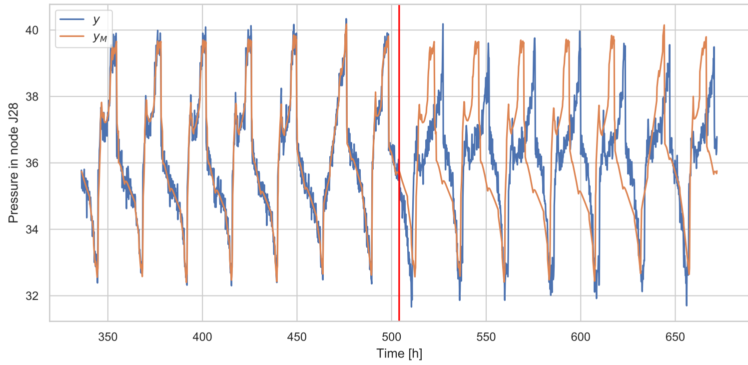

Figure 1: Pressures in node J28, measurement and model, with leak in node J29

was used. The Water Network Tool for Resilience (WNTR, pronounced winter) is a Python package designed to simulate and analyse resilience of water distribution networks. WNTR is based upon EPANET. Using WNTR it is possible to simulate network hydraulics and water quality using pressure dependent demand or demand-driven hydraulic simulation, and the ability to introduce leakages in specific network nodes.

The water supply network of the city of Walkerton was proposed as an object enabling the verification of the developed diagnostic algorithms. Walkerton is a town of about 5,000 inhabitants situated in the Canadian province of Ontario. In May 2000, the drinking water in Walkerton was contaminated with the highly dangerous O157:H7 strain of E.coli bacteria. The analysed network consists of: 310 junctions (network nodes), 358 pipes, 3 reservoirs, 3 pumps, 3 valves and 2 tanks.

Figure 2 shows a diagram of the water supply network of the town of Walkerton. The network has three water reservoirs marked with the letter R and two equalizing tanks marked with the letter Z. The pipes with a diameter of 250 mm and 300 mm, constituting the main line, are marked in red. In order to test the developed diagnostic algorithms, measurement points were placed on the water supply network. At each point, it is possible to measure pressure and flow. Blue shows the measurement points on the main bus, while the yellow color marks the measurement points on the distribution network. Of course, during the algorithm tests, it is possible to take into account only selected measurement points.

Leak simulation

Leaks were simulated using WNTR Simulator[1] and are modelled with equation [28]:

$$d_{leak} = C_d A p^{\alpha} \sqrt{\frac{2}{\rho}}, \tag{13}$$

where d_{leak} - leak demand $[m^3/s]$, C_d - discharge coefficient (unitless) ($C_d = 0.75$), A - area of the hole $[m^2]$, α - exponent related to characteristics of the leak (unitless) ($\alpha = 0.5$ - large leaks out of steel pipes), p - gauge pressure $[Pa]$, ρ - density of the fluid $[kg/m^3]$.

[1]`https://wntr.readthedocs.io/en/latest/hydraulics.html`

5.2 Metrics

The leak isolation algorithm calculates the value of a function W_{vn} for each node v_n in the network. Nodes with higher values of W_{vn} are more likely to be leak locations. Node with the highest value of W_{vn} will be called localization result node.

For numerical assessment of the quality of the proposed algorithm, we use the following metrics (based on [29]):

1. MPD (minimum pipe distance (in meters)) - length of the shortest path between the leak node and the localization result node, measured in meters along pipes in the network (it is larger or equal to geographical distance)
2. MND (minimum node distance) - length of the shortest path between leak node and localization result node, measured in number of nodes in the path
3. PR (probability ranking) - rank (position) of leak node in values of W_{vn} sorted descending, divided by the number of nodes in the network (i.e., if we search network nodes in order of descending W_{vn} function, what fraction of nodes needs to be checked before finding real leak node)

5.3 Leak scenarios

We considered two leak scenarios - leak in node J29 and J316. Both leaks were simulated with leak area $A = 0.0005$, which corresponds to leak demand flow equal to $d_{leak} = 0.009[m^3/s]$. Noise with a standard deviation of 0.25 was added to simulated pressures to make experimental conditions more realistic. Simulated leakages start at midnight; hours in all the following figures (Figs. 3 - 6) corresponds to the time since the leak started.

The leak localization algorithm is carried out each hour (residual values are calculated every 10 minutes and averaged). The leak localization algorithm was carried out with parameters: $N = 3$, $K = 1.1$, and $\tau = 1$. Only pressure measurements were used. Residuals were generated by the Holt-Winters model. Exemplary results are shown in Figs.4-6. The colour of nodes presents the value of the localization function. Node with a leak is marked with a cross and localization result node with a diamond.

It can be observed that the result of the localization algorithm highly depends on the time of localization. Our heuristic approach assumes that the value of pressure will drop (compared to the normal state) in the presence of a leak. However, it can be observed that this assumption not

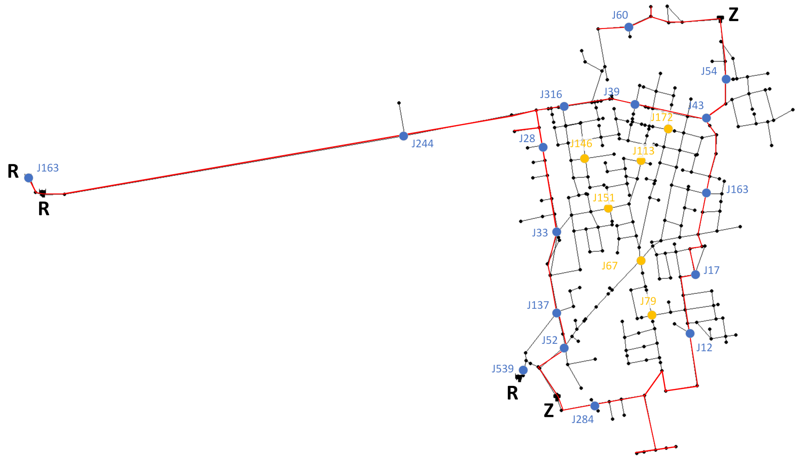

Figure 2: Diagram of the water supply network of the town of Walkerton

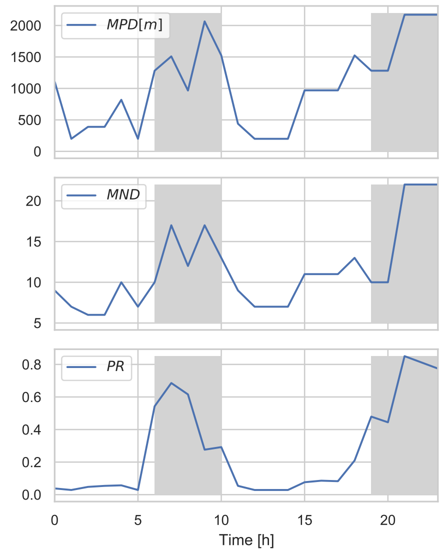

Figure 3: Time evaluation of quality metrics, hours with mean value of residuals above 0 are marked with gray rectangles

always holds (due to the action of a control system in the network) - Fig. 1 shows values of measurement and model in a node J28 in the presence of a leak in near node J29. Therefore, the localization algorithm gives reasonably good results for hours when a leak causes pressure drop - it can be observed in Fig. 4 and Fig. 6, where distances between the actual leak node and the node selected by the algorithm are respectively 105 m and 199.5 m (results may slightly vary depending on noise). Time evolution of quality metrics was presented in Fig. 3 (hours with the mean value of residuals above 0 are marked with grey rectangles).

According to this observation, we propose to use time filtering and carry out a localization algorithm only for hours with mean values of all residuals below zero (for comparison with a version without filtering, see Section 5.5).

5.4 Implementation

All algorithms were implemented in Python, the WNTR package was used for handling the water distribution network and simulation, the NetworkX package for graph processing algorithms. The Dijkstra algorithm was used for shortest path calculations.

There are many possible cases to investigate (leaks in different locations, different leak sizes, 24 hours, two algorithm parameters (K and N), noise, different sensor locations). Therefore we prepared Dash[2] application[3] to explore different scenarios, and the reader is invited to check different configurations.

5.5 Results

As a baseline for LLD, we use the algorithm proposed in [7], where current residuals are correlated with the sensitivity matrix obtained from simulation with leaks. We calculated a separate sensitivity matrix for each hour of the day. For more realistic conditions (i.e., a non-perfect simulator calibration), we simulated leaks with leak area $A = 0.0001$ and run leak scenarios with leak area $A = 0.0005$. We fully acknowledge that in the presence of a properly calibrated simulator, it is preferable to use a method from [7].

Results for two leak scenarios are presented in Tab. 1 and Tab. 2. The heuristic method proposed in this paper is denoted as LDD and method from [7] as Sensitivity Matrix Correlation. We consider scenarios without noise and with random noise drawn from normal distribution with $mean = 0$ and standard deviation $\sigma = 0.25$. Noise is added to residuals values. For noise scenarios, the presented results are averages from 10 runs. We also consider a version with time filtering - the algorithm is only carried out for hours with mean residual values below 0 (hours not marked gray in Fig. 3). Presented results are averages for 24 hours (or selected hours in version with time filtering).

It can be observed that in this set-up, our heuristic approach gives competitive results - in most cases, it is better in terms of MPD and PR metrics and worse in terms of MND. Time filtering improves the results of LDD significantly. Interestingly, some improvement with time filter-

[2] `https://dash.plotly.com/`

[3] `https://leak-localization.herokuapp.com/` - Please be patient, it can take few minutes to start up!

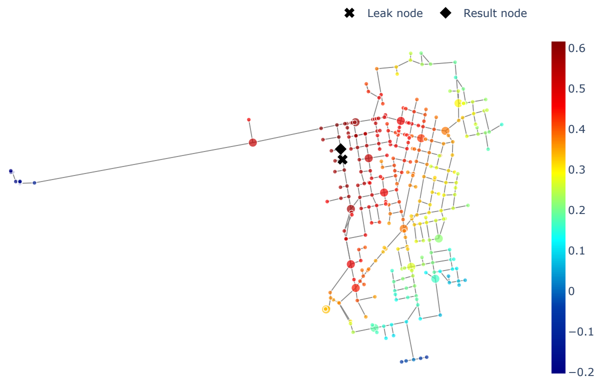

Figure 4: Leak in node J29, 1 a.m. (1 hour from leak start).

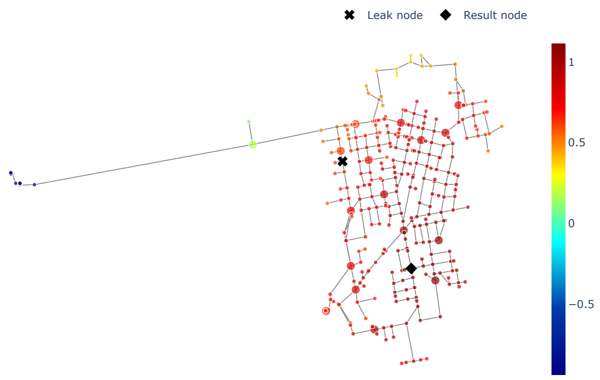

Figure 5: Leak in node J29, 7 a.m. (7 hours from leak start)

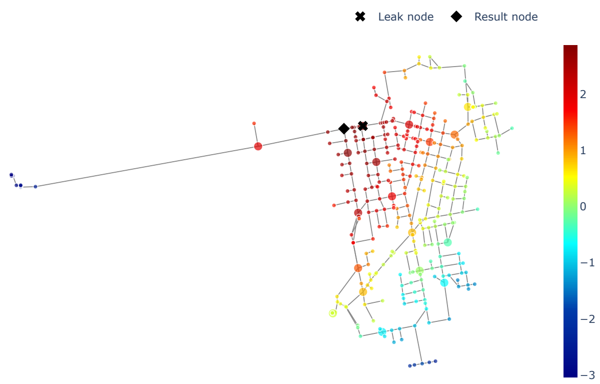

Figure 6: Leak in node J316, 1 a.m.(13 hours from leak start)

ing can also be noted for a Sensitivity Matrix Correlation method.

5.6 Relation to existing approaches

In this paper, we propose a leak localization method using only existing pressure sensors and network structure. Most of the existing approaches (see Section 2) require calibrated simulator and/or data from faulty states. Therefore our goal is to propose a method that can be applied when these are unavailable.

An interesting approach with similar assumptions (only current measurements and historical data from normal states are needed) was described in [29]. This paper uses a model based on physical equations with coefficients estimated from historical data for residual generation and kriging for taking into account nodes without measurements. The network model assumes that all demand nodes follow the same demand pattern. Our heuristic algorithm differs from the method proposed in [29] in the following aspects:

- For a residual generation, we use a Holt-Winters model, witch is computationally simpler and adaptive.
- We do not assume the same demand patterns in all consumer nodes. On the other hand, we assume that de-

Table 1: Quality metrics, leak in node J29

method	noise σ	time filtering	MPD [m]	MND	PR
LLD	0	no	1003	8.54	0.28
	0.25	no	935	8.17	0.28
	0	yes	621	4.38	0.061
	0.25	yes	595	4.54	0.076
Sensitivity Matrix Correlation	0	no	1365	6.54	0.32
	0.25	no	1470	7.96	0.35
	0	yes	787	5.06	0.14
	0.25	yes	957	7.11	0.18

Table 2: Quality metrics, leak in node J316

method	noise σ	time filtering	MPD [m]	MND	PR
LLD	0	no	1042	11.5	0.28
	0.25	no	972	11.1	0.28
	0	yes	674	8.93	0.076
	0.25	yes	630	8.27	0.086
Sensitivity Matrix Correlation	0	no	1287	8.71	0.29
	0.25	no	1500	10.1	0.31
	0	yes	453	5.66	0.10
	0.25	yes	793	7.9	0.13

mand patterns are slowly changing in comparison to the rate of change caused by leaks. Our model also does not take into account quick changes in network operating conditions.

- In LLD, there is no need to estimate pressures in normal working conditions in all network nodes.

6 Conclusions

This paper shows preliminary results for a leak localization algorithm that uses only pressure (or flow) measurements and network structure. A water distribution network simulator is not needed. When tested in simulation our algorithm gives promising results. In the further stage of the project, we plan to test it with real data. Leak localization in the case of limited measurement and lack of a properly calibrated simulator is a very challenging task. On the other hand, there are real-life scenarios, where such an algorithm is needed. Therefore we see further research directions:

- providing mechanism to cope with high time variability of results,
- testing with real data,
- developing other localization algorithms with similar assumptions,
- testing different residual generation methods.

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