DECOMPOSITION-BASED DATA ANALYSIS WITH HYDRAULIC MODEL CALIBRATION FOR LEAKAGE DETECTION AND ISOLATION

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SUMMARY

This paper proposes an integrated approach for leak detection and localization. The leak detection is undertaken by data analysis in multiple steps including time series data decomposition to ensure stationarity, leakage event detection by statistical process control methods using the correlation analysis of multiple sensor events of monitored flows and pressures. A detected leak event is localized via hydraulic model calibration with the snapshots of flow and pressure data collected during the leakage event. The approach is applied to L-Town with two-year monitoring data and the hydraulic model. The results show that the proposed method is effective at detecting and localizing both incipient leaks and pipe bursts.

Keywords: Data decomposition, statistical process control, leakage detection, model calibration, leakage localization

INTRODUCTION

Water distribution systems have been monitored by using conventional Supervisory Control and Data Acquisition (SCADA) technology, by which key control facilities, such as pumps, tanks, service reservoirs and water treatment plants, are monitored to facilitate and automate the operation of critical control components. Over last decade, with advancement of emerging technologies, especially cost-effective sensors and ubiquitous internet connectivity, more and more smart meters, sensors and data loggers are deployed for monitoring water distribution systems. Large amount of data or often referred to as big data, is collected for enabling smart water network operation and management. One important system operation task is to detect the abnormal conditions or so-called anomaly events that are captured by and embedded in flow and pressure time series data. An anomaly event can be either unauthorized (or illegal) water usages or a new pipe burst with and without (hidden underground) overflow in streets. It is the unauthorized water usage and the pipe burst that must be detected and localized for operators to pinpoint the anomaly event hotspots in the field and subsequently take proper actions to mitigate the impact of such an event. Therefore, it is imperative to detect and localize the anomalies by analyzing the time series data of flows, often recorded at the inlets of a system or District Meter Area (DMA) and the pressures within a water distribution system.

In general, anomaly detection is the identification of rare items, events or observations, which raise suspicions by differing significantly from most of the data. Over last decades, a lots of research works have been conducted for water distribution system anomaly detection. Comprehensive reviews (Mounce and Boxall 2011; Wu and Liu 2017) have been conducted for this research topic. In general, three types of methods, including prediction-classification (PC) approaches; clustering algorithms (CA), and statistical process control (SPC) methods, have been developed and applied to water distribution anomaly detection. In this paper, we propose an approach integrating the data decomposition based SPC with hydraulic model calibration for the battle of leak detection and location (Vrachimis et al. 2020).

METHOD FORMULATION

The proposed approach proceeds with time series data decomposition, anomaly (leakage) event detection and event localization. Each of the tasks is briefly elaborated as follows.

Data Decomposition

To effectively apply data analytical methods such as SPC methods for event detection, it is essential to ensure that time series data is stationary, that is, the mean and variance of the dataset do not change over time. Since a typical flow or pressure data contains daily, weekly and monthly seasonality, it is nonstationary data. Therefore, flow and pressure time series are decomposed to get rid of the influence of trend and seasonality. The original value (O) will be decomposed into three series including seasonal component (S), trend component (T), and remainder component (R), given as:

$$O(\mathrm{t}) = R(\mathrm{t}) + S(\mathrm{t}) + T(\mathrm{t}) \qquad (1)$$

An improved version of the Seasonal-Trend decomposition procedure based on Loess (STL) (Cleveland et al. 1990) has been employed to decompose the raw data.

Leakage Event Detection

Leak detection is undertaken by conducting data analysis that is based on SPC with decomposition of the time series data. Specifically, the event detection is conducted for detection of two types of leakage events including (1) incipient leak that usually starts with a very small size and grows over time, and (2) pipe bursts that occur abruptly. To detect an incipient leak, SPC analysis is conducted with trend component T(t) while the pipe burst detection is undertaken by applying SPC with the remainder component R(t).

Leakage Localization

Whenever a leakage event is detected, the snapshot of dataset is imported into the calibration tool for localizing the leak by pressure dependent leakage detection (PDLD) method (Wu et al. 2010) via hydraulic model calibration with the pressure and flow monitoring data collected for the event. The PDLD method is formulated to search for the likely anomaly hotspots that are emulated as emitters at nodes where unauthorized water usages or leaks are modeled as pressure dependent demands in addition to real consumptions. The emitter locations and coefficients at possible anomaly nodes are the decision variables to be optimized such that the difference between the simulated and field observed pressures/flows is minimized. Identifying and quantifying leakage emitters are effectively part of the model calibration effort to represent additional pressure dependent demands (e.g. leaks) in a hydraulic model.

APPLICATION

The integrated method has been applied to each of areas A, B and C for leakage detection and localization of L-Town (Vrachimis et al. 2020).

Flow Data Preparation

Total inflow into a system is the primarily data feature for leakage event detection. As a leakage is the extra ‘consumption’ in addition to the real water consumptions throughout the system. The net inflow into each area must be correctly prepared for leakage detection and isolation.

Area A and B

The net inflows into area A and B are worked out by subtracting the pump (Pump_1) flow from the outflows of two reservoirs (R1 and R2). With a PRV installed at the inlet of area B and only one pressure data point, the analysis is performed by decomposing the pressure time series data at n215.

Area C

The inflow for area C, noted as Q_c(t) is given as:

$$Q_c(\mathrm{t}) = Q_{tank}(\mathrm{t}) - Q_{amr}(\mathrm{t}) \qquad (2)$$

Where Q_{amr}(t) is the sum of Automated Metered Readings (AMR) installed in area C and Q_{tank}(t) is the outflow from the tank. Q_{tank}(t) is derived by solving for the mass balance of tank volume using the recorded pump flows (as the tank inflows) and the tank levels. Assume $Q_{pump}(t)$ be the pump flows at time t and tank level be noted as $L_{tank}(t)$. For each time step of Δt from time t_1 to t_2, the flow balance is given as:

$$\int_{t_1}^{t_2} [Q_{pump}(t) - Q_{tank}(t)]dt = \pi r^2 [L_{tank}(t_2) - L_{tank}(t_1)] \quad (3)$$

Where r is the radius of the tank. With the recorded tank levels and pump flows (as tank inflows), tank outflows or the inflow into area C can be solved with Eq. (3).

Constructing Detection Model

Using the flow and pressure data provided for 2018, the leakage detection model is constructed by decomposing the time series data to obtain the seasonality components, noted as $S_{d,i}$, $S_{w,i}$, $S_{m,i}$ for daily, weekly and monthly seasonality, of sensor i respectively. X-bar method is applied to the remaining data, the sum of remainder $R(t)$ and trend $T(t)$ for each sensor, to establish the leakage event detection control chart with 3σ control limits. One control chart is established for one sensor or each time series (inflow and pressures at various locations). A leakage event is detected when the flow data is above the upper control limit and/or the pressure is below the lower control limit. Fig.1 shows the example of inflow control chart for area A and B. The 3σ control limits are established for the 24-hour inflow trend change. Starting time of a leak event is detected when the trend change is above the upper limit, the end of the leakage event or maintenance completion is detected when the trend change is below the lower limit. As illustrated, all the historical events for 2018 have been detected along with some unreported or undetected small events have also been detected. Similarly, control charts have been constructed for area C to detect the leakage events as shown in Figure 2. Both incipient leaks and pipe bursts have been successfully detected for the system.

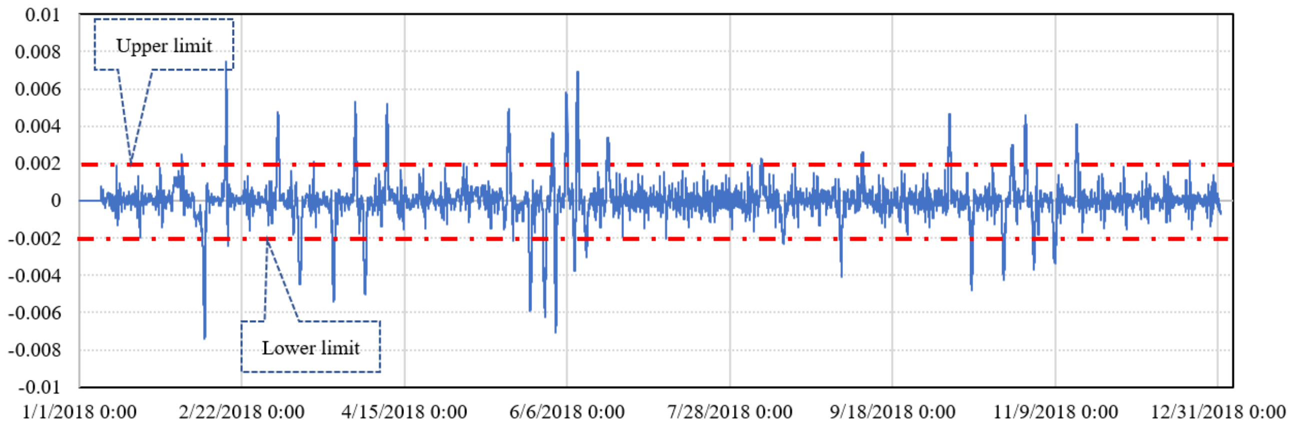

Figure 1 Inflow control chart for detecting 2018 historical events (pipe bursts) in Area A and B

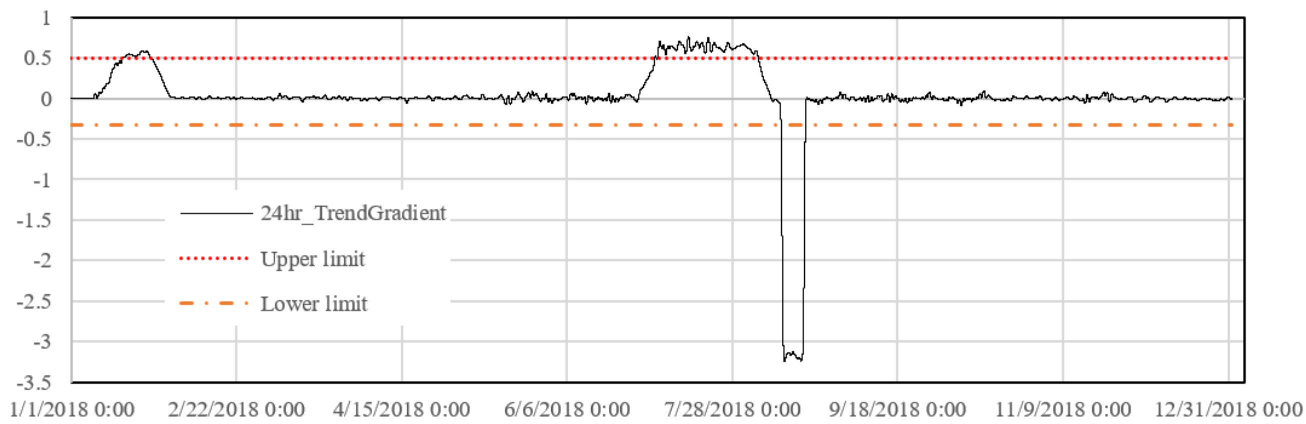

Figure 2 Inflow control chart for detecting 2018 historical events (incipient leaks) in Area C

Testing and Evaluation

Using the control charts established with the historical data (the given dataset and leakage records for 2018), and assuming 2019 dataset as provided for model testing and evaluation be made available once a day, namely every 24 hours, the leakage event detection is conducted by applying the control chart in a rolling forward manner every 24-hour with the dataset for each sensor. The inflow is used as primary data for leakage event detection. Once an event is detected, the snapshot of data, including the inflow and pressures, are automatically imported, via the SCADA Simulator tool (Bentley 2019), into the latest version of optimization-based model calibration tool (Bentley 2019), as shown in Figure 3 and 4, and the likely leakage hotspots are localized via PDLD method (Wu et al 2010). Table 1 summarizes the all the leakage events detected and localized for 2019.

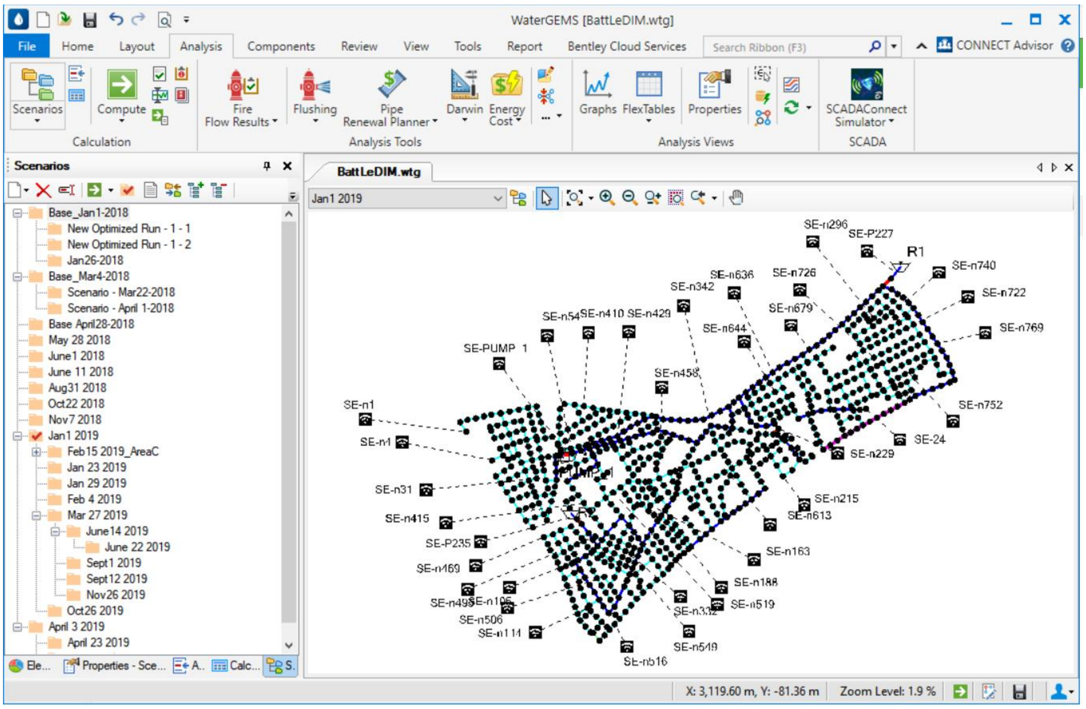

Figure 3 Hydraulic model for leakage event localization

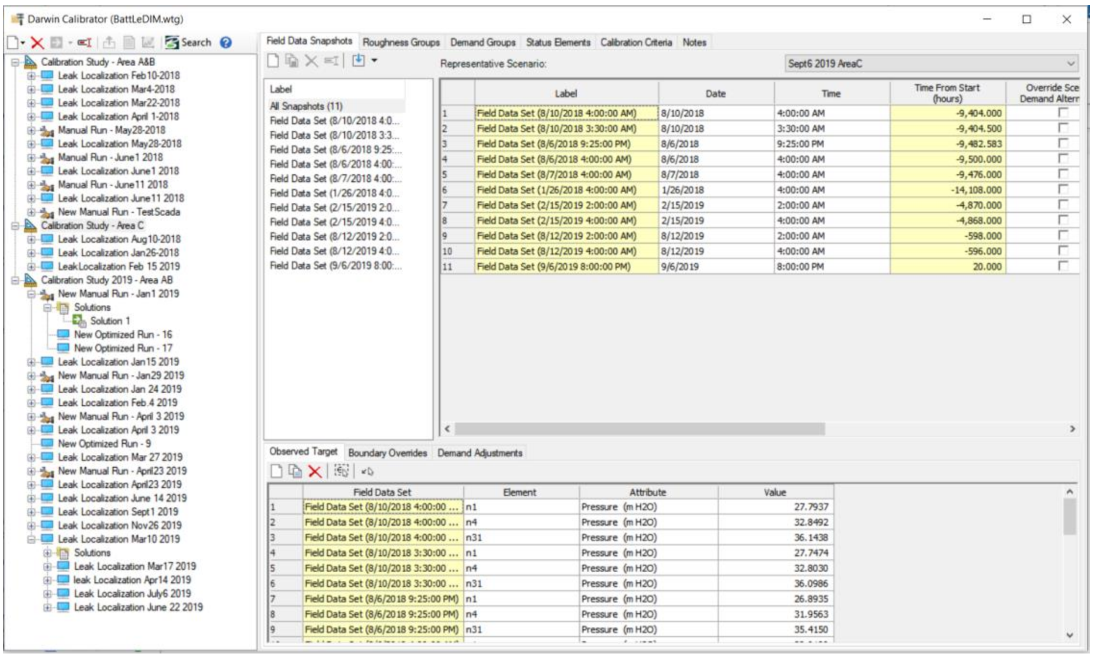

Figure 4 Illustration of model calibration-based leakage event localization for 2018 and 2019 events

Table 1 Summary of detected events and localization

Link ID	Start Time	Link ID	Start Time
p587	1/15/2019 19:00	p308	6/17/2019 8:50
p832	1/24/2019 14:40	p366	6/22/2019 22:05
p309	2/7/2019 21:40	p795	6/22/2019 22:05
p57	3/9/2019 23:05	p658	6/22/2019 22:05
p208	3/16/2019 23:45	p85	7/6/2019 23:25
p781	3/24/2019 1:25	p61	7/6/2019 23:25
p691	3/27/2019 1:25	p726	7/10/2019 11:45
p204	4/2/2019 17:30	p599	7/10/2019 11:45
p745	4/2/2019 17:30	p325	7/10/2019 11:45
p379	4/2/2019 17:30	p146	7/10/2019 11:45
p412	4/20/2019 6:30	p716	8/17/2019 23:45
p576	4/20/2019 6:30	p424	8/17/2019 23:45
p41	5/19/2019 2:05	p116	8/23/2019 19:05
p402	5/19/2019 2:05	p366	10/25/2019 13:40
p430	5/19/2019 2:05	p459	11/17/2019 1:05
p393	6/12/2019 16:00	p670	11/30/2019 22:45
p691	6/12/2019 16:00	p518	11/30/2019 22:45

CONCLUSIONS

An integrated approach has been developed for (incipient and pipe burst) leak detection and localization. The flow and pressure time series data is first decomposed into multiple three components and analysis has been performed with the stationary elements (trends and remainders), which is analyzed with the SPC method. The detected events are localized by applying the well-developed PDLD method via hydraulic model calibration. While the proposed approach has proven to be effective at detecting and localizing the leaks with the computer simulated data, the time series data collected from the field can be different from the simulated data. The challenges remain in detecting and localizing the leaks by dealing with the real data for a real-world system.

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