



SENSOR NETWORKS FOR MONITORING AND CONTROL OF WATER DISTRIBUTION SYSTEMS

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ABSTRACT

Water distribution systems present a significant challenge for structural monitoring. They comprise a complex network of pipelines buried underground that are relatively inaccessible. Maintaining the integrity of these networks is vital for providing clean drinking water to the general public. There is a need for in-situ, on-line monitoring of water distribution systems in order to facilitate efficient management and operation. In particular, it is important to detect and localize pipe failures soon after they occur, and pre-emptively identify 'hotspots', or areas of the distribution network that are more likely to be susceptible to structural failure. These capabilities are vital for reducing the time taken to identify and repair failures and hence, mitigating impacts on water supply.

WaterWiSe is a platform that manages and analyses data from a network of intelligent wireless sensor nodes, continuously monitoring hydraulic, acoustic and water quality parameters. WaterWiSe supports many applications including dynamic prediction of water demand and hydraulic state, online detection of events such as pipe bursts, and data mining for identification of longer-term trends. This paper describes the WaterWiSe@SG project in Singapore, focusing on the use of WaterWiSe as a tool for monitoring, detecting and predicting abnormal events that may be indicative of structural pipe failures, such as bursts or leaks.

KEYWORDS

Water distribution systems, wireless sensor network, online event detection, localization, pressure transients

INTRODUCTION

Drinking Water Distribution Systems (WDS) carry potable water from water sources (reservoirs, water tanks) to industrial, commercial and residential consumers through complex pipe networks. An adequate water supply (in terms of availability and quality) is vital to performing many daily tasks, and disruptions to a water supply through planned maintenance or leakage repairs can cause significant problems. Urban population growth adds to the demands on the water supply infrastructure. Utilities are faced with increasing costs of installing new pipelines to serve the growing population as well as maintaining and replacing the aging system. Increases in pumping, treatment and operational costs are pushing water utilities to combat water loss by developing methods to detect, locate and fix leaks.

Leaks and bursts are an unavoidable aspect of water distribution systems management, and can account for significant water loss within a distribution network if left undetected for long periods. For example, in the United States, an estimated 7,000 km of pipe requires replacement each year at a cost of around \$2.7 billion while water losses are (estimated to be 10%) cost around \$4.3 billion per year (USEPA 2007); countries such as England, France and Italy report water losses in the 20–30% range (VEWA 2006). In the United States, there are an estimated 237,600 pipe breaks per year (USEPA 2007). Leaks often occur through a build up of corrosion that causes structural failures in aging pipes, particularly at joints. For water utility operators, the ability to detect and localize pipe bursts and leaks quickly is important: bursts can occur in pressurised water transmission mains and distribution pipelines, and can be costly in terms of repair and damage to surrounding property and facilities. In addition, such failures can have significant social and environmental impacts (e.g., service interruptions, traffic delays, lost water and energy) (Whittle et al. 2010). For example, recently two US cities faced major failures in their water distribution systems:

During the summer of 2009, Los Angeles experienced a series of pipe breaks and leaks that caused significant disruption. An expert review report presented to the city attributed the pipe breaks to pressure drops associated with a regimen of water rationing introduced in Los Angeles. In light of the absence of direct pressure monitoring data, however, this finding remains largely speculative. In May 2010, a huge main rupture in Boston caused two million residents of the greater Boston area to lose clean drinking water, prompting a state of emergency. The backup water supply did not meet US Environmental Protection Agency (USEPA) standards, and the public was without usable drinking water for several days. The lack of a real-time monitoring regimen for water quality caused a delay because data had to be collected analyzed before authorities could assure residents in Boston and dozens of surrounding communities that the water was again safe for consumption.

There are two general complementary strategies for dealing with pipe bursts and pervasive leakage problems: 1) development of condition assessment tools that can identify existing leaks or evidence of pipe deterioration and hence, support rational asset management programs; and 2) monitoring systems that can detect and localize underground burst events or sources of long-term water losses, enabling implementation of timely mitigation and repair. There has been a great deal of research and development on condition assessment/NDE technologies for underground pipelines using electromagnetic (e.g., eddy current, ground penetrating radar etc.) and mechanical (e.g., acoustic emission, ultrasonic etc.) methods (Rizzo 2010). Most of these methods are limited to periodic/infrequent inspections of the massive urban-scale pipeline networks, or can be used for localized detection in targeted areas. In contrast, there has been almost no development of online monitoring systems that can enable remote detection of events. To date the most detailed data about the current state of the water network in terms of flow, pressure and water quality is gathered using Supervisory Control And Data Acquisition (SCADA) systems located at reservoirs or water tanks. There is generally very limited on-line monitoring and analysis capabilities deployed on the pipes and valves within water distribution networks. For example, pressure and water quality are spot-checked to comply with regulations or to deal with customer complaints, while background leakage surveys are performed periodically around the system (typically using mobile acoustic leak detection devices). Since the pipes in a water distribution network are pressurized, events such as pipe bursts, valve opening/closure can be detected remotely as pressure transients distinct from the background pressure signals.

Wireless sensing technology has advanced to the point that the deployment of dense networks of low-cost devices for real-time infrastructure monitoring is now feasible. When combined with appropriate data processing techniques, the increased density and availability of these measurements enables improved response, management and prediction of infrastructure failures. WaterWiSe is a platform for water distribution systems operators providing real-time monitoring and decision support tools (Allen et al. 2011, Whittle et al. 2010) that can be used to help improve system management and operation. WaterWiSe uses a combination of model-based prediction and data stream analysis as a basis for its decision support tools. The primary data source is a wireless sensor network (WSN) that is deployed on the pipes within the distribution system, providing on-line updates of the hydraulics and water quality. The technology has evolved from an earlier prototype deployed in Boston (Stoianov et al. 2006, Stoianov et al. 2007). The WaterWiSe project was initiated in 2008 by the Singapore-MIT Alliance for Research and Technology and Singapore's Public Utilities Board (PUB) to improve the state of the art with respect to in-situ, real-time sensing and modeling of water distribution systems. WaterWiSe has been deployed in Singapore since 2009, and has scaled from a proof-of-concept 8-node network collecting only pressure data to a 50 node network covering several supply zones (with an area of 80km²), with online measurements of pressure, flow, acoustics and a variety of water quality parameters and providing decision support tools that are used in day-to-day operations of the water distribution system.

The wireless sensor network has been used as a live research test-bed for the development and refinement of algorithms for leak and burst detection and localization. During its development and expansion over four years, WaterWiSe has accumulated a large archive of sensor data from sensor nodes. This archive has proved an invaluable resource on which to perform exploratory data mining to identify common patterns and trends, and to help identify areas of concern in the network that warrant further, in-depth investigation. It is also helpful for post-mortem analysis of response to events, where the actions that were taken can be matched to data streams and used to help inform future actions.

This paper describes the WaterWiSe platform used in the WaterWiSe@SG project, focusing on its capabilities to i) detect and localize bursts, and ii) identify *hotspots*, areas at risk of leaks and bursts in the network. First, the WaterWiSe system is described; second, the algorithms used to detect and localize bursts are presented, along with experimental performance measurements. Next, the *hotspots* approach is described and some examples of abnormal events are presented.

THE WATERWISE PLATFORM

The WaterWiSe platform consists of three layers: an on-line wireless sensor network, the Integrated Data and Electronic Alerts System (IDEAS), and the Decision Support Tools Module (DSTM). The WSN is deployed in-network, and provides on-line streams of data. The IDEAS layer processes data streams from the WSN to detect and localize abnormal events (for example, leaks or water contamination events). The DSTM layer provides a suite of decision support tools that utilize an on-line, calibrated hydraulic model of the water distribution network.

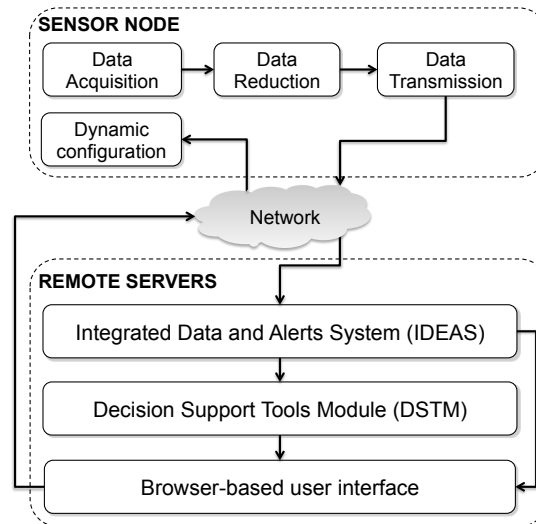


Figure 1. - The relationship between WaterWiSe's layers: IDEAS and DSTM run on remote servers, supplied with data by the wireless sensor network (sensor node). The browser interface provides users with a way to interact with IDEAS, DSTM and reconfigure the sensor nodes.

WaterWiSe can operate as a stand-alone system as well as a component in an integrated water management system. In stand-alone mode, a map-based web interface and dashboard is provided to both IDEAS and DSTM (see Figure 1). This user interface is accessible through the web-browser on regular desktop PCs as well as tablet and smart phone, allowing for in-field analysis and validation by the field crew. WaterWiSe is either hosted locally within a water utility or over the Internet via the cloud.

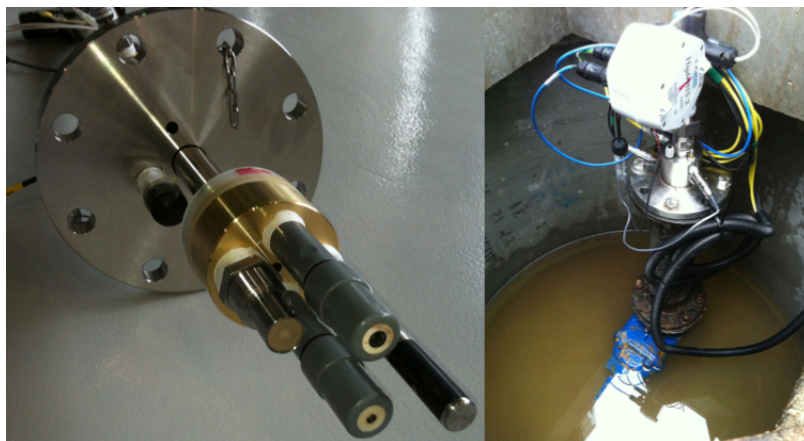


Figure 2. – WaterWiSe multi parameter sensor probe (left), and the probe attached to a gate valve (right)

Wireless Sensor Network

Each sensor node in the WaterWiSe network is based around a 72MHz ARM Cortex M3 CPU with 64KB of RAM, a 2GB SD card for storage, a GPS with pulse-per-second functionality for time synchronization, and a 3G modem for data transmission. Nodes do not currently operate in an ad-hoc multi-hop network because in practice, the average inter-node distance of 500 to 1500m tends to be greater than 802.15.4 or 802.11 class radios can reliably transmit in an urban environment. The 3G modem gives typical upload speeds of around 4-5KB/s, which is more than adequate for the data generated. Sensors are interfaced to the node using a custom I/O board that supports hydraulic parameters (pressure, hydrophone, flow), and water quality (pH, conductivity, temperature, Oxidation Redox

Potential [ORP] as a proxy for free chlorine and electrical conductivity). Sensor nodes are powered by a 33Ah 12V battery, which is charged either by a solar panel (during the day), or by an AC line taken from a nearby lamppost (from 7pm to 7am). The sensor node is stored in an enclosure with its batteries and mounted on a pole. Hydraulic and water quality sensors are mounted on an integrated multi-probe that is inserted into the water pipe via a gate valve. Figure 2 shows an example multi-probe and sensor node deployment.

WaterWiSe nodes can be remotely and dynamically configured to sense and transmit data in a variety of ways. Individual parameters are typically sampled at intervals relevant for their expected rates of change, and transmitted at rates relevant for the applications they may serve. Hydrophone data is used to detect background leakage, and is sampled at kHz rates, but only gathered for a few seconds every hour. Pressure data is continuously sampled at hundreds of Hz in order to capture transients that are indicative of pipe bursts. Data is either transmitted in 30-second windows of raw samples, or processed locally using an IDEAS event detection algorithm so that only event notifications and short data traces are sent. Water quality parameters, flow and battery data are typically sampled at 30s intervals, aggregated, and transmitted every 5 minutes.

The remote server acknowledges data transmissions - unsuccessful transmissions are retried, and network or radio failures trigger reconnections and eventually radio power cycling. When reconfiguration commands need to be passed to nodes, they are passed at the end of a successful upload. Nodes can buffer several days of data in the event of a network outage, and prioritize lower-rate data when network connections have low-bandwidth. Sensor node data is typically synchronized to within 0.5ms of GPS.

Each sensor node consumes 0.036W when in sleep mode, 0.75W when sampling, and 4.5W when transmitting data over 3G. Whilst the device is not intended to be ultra-low power due to high sampling rates, energy can be conserved through software configuration when battery-charging options are limited.

Integrated Data and Electronic Alerts System (IDEAS)

IDEAS is responsible for data stream management, processing and alert notification. On-line data from the WSN is archived as it arrives along with data from other sources such as a utility's SCADA system, or operational information such as valve closures and pump schedules. IDEAS has a set of analytics that are applied to data streams in order to detect abnormal events and provide location estimates. Detection of an abnormal event triggers an alert to be sent via e-mail or SMS to subscribed users of WaterWiSe. Figure 3 shows the user interface to IDEAS, where real-time data streams from all sensors can be reviewed, as well as alert notifications. The specific analytics applied depends on the parameters being processed (pressure, acoustics or water quality), but the basic data flow is common: abnormal events are detected in the data stream of each sensor node and are grouped together and used to estimate the location of the abnormal event.

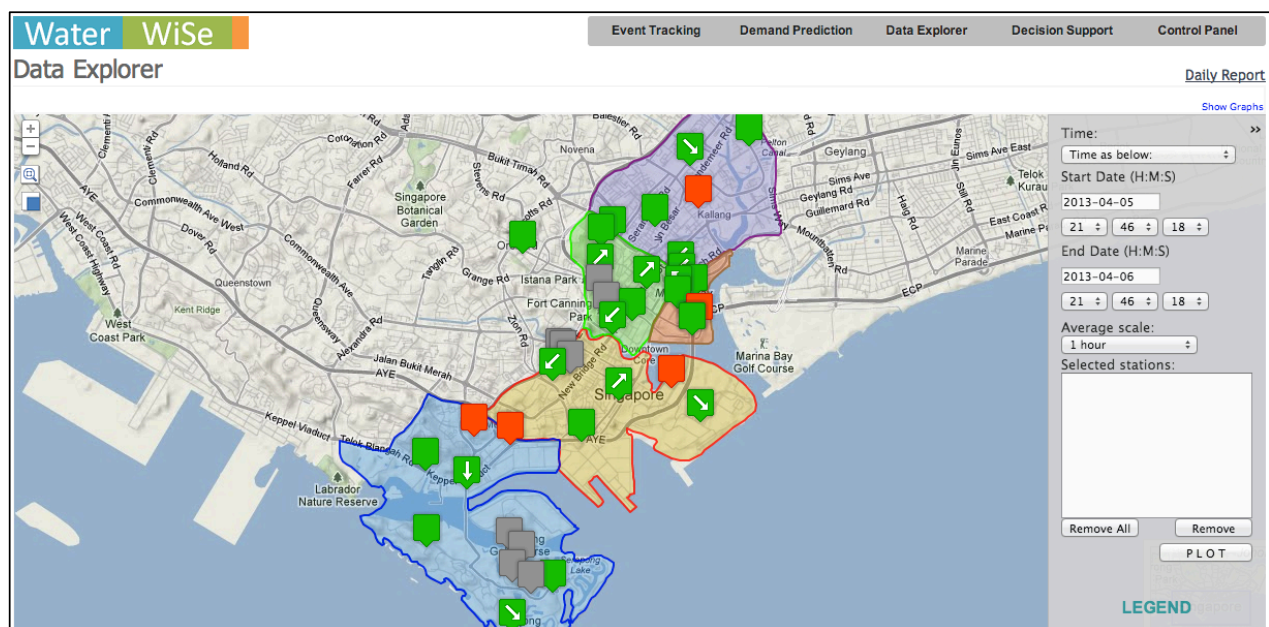


Figure 3. – The WaterWiSe user interface showing station locations overlaid on a map

Decision Support Tools Module (DSTM)

DSTM uses the sensor data streams provided by IDEAS as input to decision support tools that model the water network as a set of demand-zones. At the core of DSTM is a real-time hydraulic model of the water distribution system (EPANet model) that is calibrated at intervals as short as every 15 minutes (Preis et al. 2010, Preis et al. 2011). The calibration process uses the most recent pressure and flow data from sensor nodes along with a baseline demand pattern and seasonal information to estimate the consumption for each demand-zone in the network model. To improve user confidence in the model, the user can compare model predictions with the actual data that was collected in a given time period. The on-line hydraulic model enables several decision support tools: on-demand valve operation simulation, demand prediction, water age and source analysis, and pump optimization.

The operation simulation tool can be used by engineers to analyze the potential impact on the network of an operational event, such as valve closures and pipe isolations. The simulation interface allows the engineer to select one or more valves to isolate and determine the times for which these valves will be closed. When it has completed, the simulation results are presented, identifying pipes that will have low or reversed flow, areas that will have abnormally low or high pressure, and customers that will be isolated by the operation.

Using the demand prediction tool, water consumption can be predicted in advance for a 24-hour rolling window. Predictions can be shown on a daily summary, with comparison to the actual consumption, across the whole zone or in specific sub-zones. Water age in the system can be predicted and compared against the real-time water quality measurements being taken in the system. This helps to identify areas of high water age that may be of concern. In systems where water is pumped to consumers or storage tanks, WaterWiSe can help reduce cost and energy consumption by optimizing the pump operation schedule based on electricity tariffs, a pump's efficiency and predicted water consumption in the system.

DETECTION AND LOCALIZATION OF BURSTS

An important component of WaterWiSe is the ability to detect and localize pressure transients associated with bursts, leaks or valve operations. Pressure transients travel at wavespeeds ranging from 500 – 1400m/s (depending on pipe materials and wall thickness) and localization depends on accurate detection of arrival times at the time-synchronized sensor nodes. The source of the transient can be localized when there are multiple detections of the same event by matching the arrival times from the detecting sensors to theoretical arrival times of all junctions in a graph model of the pipe network (Srirangarajan et al. 2010). The set of most likely junctions are indicated to the user on the WaterWiSe map for further analysis.

Pressure characteristics of bursts

Many events of interest in a water distribution system, such as bursts, leaks or valve operations can be detected as pressure transients. Slow leaks, valve and other maintenance operations typically result in transients that can be detected over a time scale of minutes or hours. Conversely, pipe burst events result in pressure transients that must be detected over time-scales from milliseconds to seconds (Tullis 1989). Pipe breaks and bursts occur in pressurized water pipes over time due to the cumulative effects of corrosion, structural fatigue (due to fluctuations in fluid pressure) or external environmental factors associated with ground movements or third-party impacts (surface loading etc.). As pipes age, they become increasingly susceptible to bursts and leaks (Pearson et al. 2005). Pipe burst events result in a sudden change in the flow through the pipe producing a pressure transient which propagates along the pipeline. This pressure pulse travels in both directions away from the burst origin at the speed of sound in water (wave speed of the pipe) (Misiunas 2005). Pipe junctions and endpoints in the physical network reflect the pulse, and its speed is altered by the pipe material and diameter as it travels through the network (Young, Boulos and Wood 2007). The transient is also attenuated by friction in the pipes, causing dispersion that reduces the slope or steepness of the transient wavefront (Bergant et al. 2008a, Bergant et al. 2008b).

The burst (and subsequent leak) also creates distinct acoustic emissions, changing the background acoustic signature of the pipe. There is a significant literature and established practice for determining accurately the location of existing leaks using the cross-correlation of ground level (microphone) or insertion-based (hydrophone) acoustic measurements (Brennan et al. 2006, Hunaidi et al. 2004). However, in order to detect and localize instantaneous burst events (and hence, give a starting point to accurately locate the leak), it is advantageous to use pressure measurements. This is because acoustic signal attenuation increases with frequency and the frequency of acoustic emissions can extend into the kilohertz range depending on factors such as pipe material/size and soil type. In addition, the lower frequencies are significantly affected by environmental noise, such as that from vehicles and pumps. Thus, acoustic detection techniques are effective only within few tens of meters of the leak (Loth et al. 2004).

On the other hand, pressure transients are less readily attenuated and the pressure signature is relatively unaffected by background noise increasing the distance over which they can be reliably detected (Srirangarajan et al. 2012).

WaterWiSe's IDEAS layer is capable of using a variety of different techniques to detect transient events that are indicative of bursts. The two most-used detection techniques are described in this section: the first is based around the wavelet decomposition of the pressure signal, and the second is based around time domain series analysis.

Event detection through wavelet decomposition

In wavelet analysis, a one-dimensional signal is mapped into a time-scale representation using a bank of bandpass filters (Daubechies 1990). Wavelet analysis for singularity or transient detection has been used with many types of time-series data such as seismograms (Zhang et al. 2003) or pulmonary microvascular pressure signals (Karrakchou and Kunt 1995), as well as detection of pressure transients in for leak detection and location in water pipelines (Stoianov et al 2001).

The wavelet event detection technique used in WaterWiSe is based on multi-scale analysis of the pressure signal to detect transients (Srirangarajan et al. 2010). It has the following steps:

- Apply wavelet de-noising (to remove impulsive noise in pressure stream)
- Compute the wavelet decomposition of de-noised signal
- Identify signal features
- Determine temporal consistency of signal features across wavelet scales
- Classify signal features to determine if event or not
- Focus on transient arrival time

Due to the impulsive nature of noise present in the pressure transients, the first step in this analysis is to apply wavelet de-noising. The second step is to obtain the wavelet decomposition of the de-noised signal: the resulting wavelet coefficients are then used to identify relevant features at a range of time/frequency scales. This is done to ensure a temporal consistency across scales, and to differentiate between coherent signal features and noise. The focusing algorithm determines the arrival time of the pressure transient at the measurement points starting from a rough estimate. Multi-scale analysis is important for wavelet detection, since the signals being detected will always be corrupted with noise that i) create ambiguity at finer detail coefficient scales, and ii) blur together at coarser scales to create an inaccurate position estimate.

Event detection through time-domain statistical analysis

The time-domain event detection technique uses a set of statistical heuristics to detect transient events as well as estimate their duration and magnitude. The algorithm attempts to adaptively estimate the background noise in the pressure trace and account for this when deciding whether a transient is abnormal or not. It has the following steps, applied over windowed segments of pressure data:

- Detect transient
- Coarse classification to filter noise relative to the shorter/immediate time-scale
- Fine classification to filter noise relative to the longer time scale

The heuristics for detection and classification were developed through analysis of high rate pressure streams from the WaterWiSe archive. They attempt to filter the stream to pick out fast, large transients and suppress smaller ones.

The two techniques are complementary and have different uses within the WaterWiSe system – the wavelet detection can provide excellent time resolution for sharp (sub-second) transient events, and the time domain heuristics are useful to detect transient signals at varying time scales and collect meta-data about their features. Other techniques, such as monitoring the joint time-frequency of a pressure signal have also been used in WaterWiSe (Zan et al. 2011).

Localization algorithms

The IDEAS layer in WaterWiSe uses a graph-based search algorithm that incorporates the arrival times of transient detections at the sensor nodes to localize the event. The search algorithm is split into a coarse global search and (optionally) a fine local search.

When several detection time estimates of burst events arrive in quick succession from several different nodes, it can be assumed they relate to the same event. Consequently, these observations can be fused to provide an estimate of the burst location within a defined search space. Because a pipe burst can only occur on a pipe within the boundaries of the pipe network, the search space is more constrained than a general localisation problem. In this case, it is appropriate to use an undirected graph to model the pipe network and define a search space.

In the graph model of the network, vertices represent either pipe junctions (connections between pipes), waypoints on curved pipes or sensor locations. Edges between vertices represent pipes, and edge weights are travel time. Travel time is determined by dividing the known pipe length by the wave speed. In order to localize an event using the graph, the burst transient must be detected at two or more measurement points.

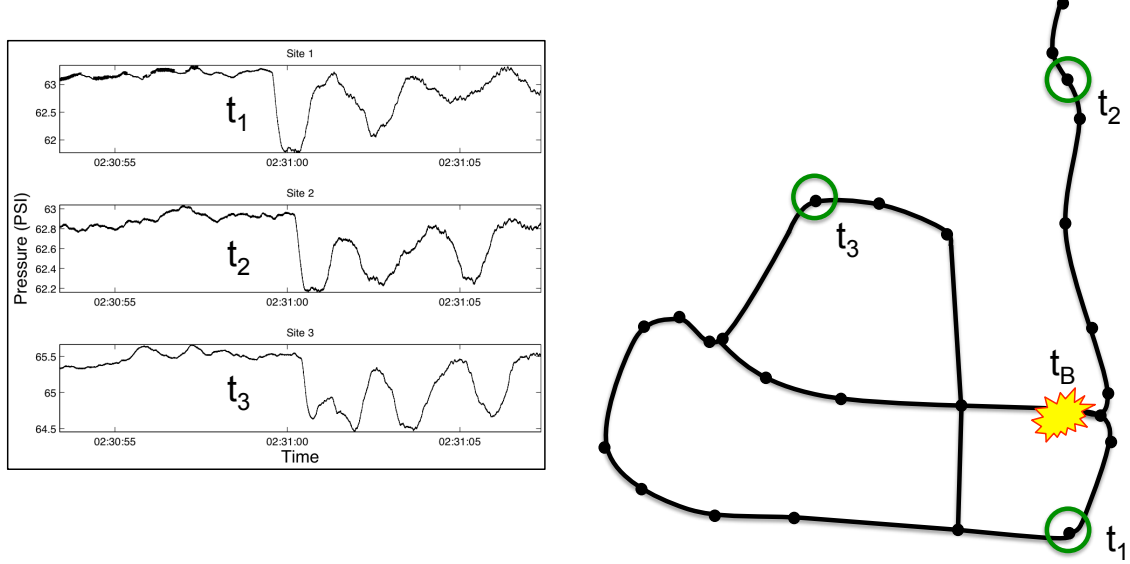


Figure 4. - A simplified visualisation of a pipe network as a graph showing detection times (t_1 , t_2 , t_3) at sensor nodes and the burst location (t_B). Pressure traces with transients are shown for context.

The detection times from each node represent the times that the transient arrived at the node (the *time-of-arrival*). The problem is to find the vertex that is the most likely location of the burst, given multiple time-of-arrival estimates from sensor nodes within the network. Assume the burst event occurs at time t_B and is detected at nodes j and k at times t_j and t_k respectively. The travel times from the burst location to the measurement points ($t_j - t_B$) and ($t_k - t_B$) cannot be determined, however the difference between the arrival times ($t_j - t_k$) is known. It is also possible to calculate the shortest travel time τ_{jk} between any two vertices j and k in the graph, e.g., using Dijkstra's algorithm (Dijkstra 1959). So, if the burst occurs at vertex i , where $i = 1 \dots N$ (N = the number of vertices in the graph), it follows that:

$$(t_i - t_k) - (\tau_{ij} - \tau_{ik}) = 0 \quad (1)$$

However, due to timing, measurement and other errors, the left-hand side of the equation is unlikely to be zero. The most likely burst location is determined by minimizing the following metric over the search space:

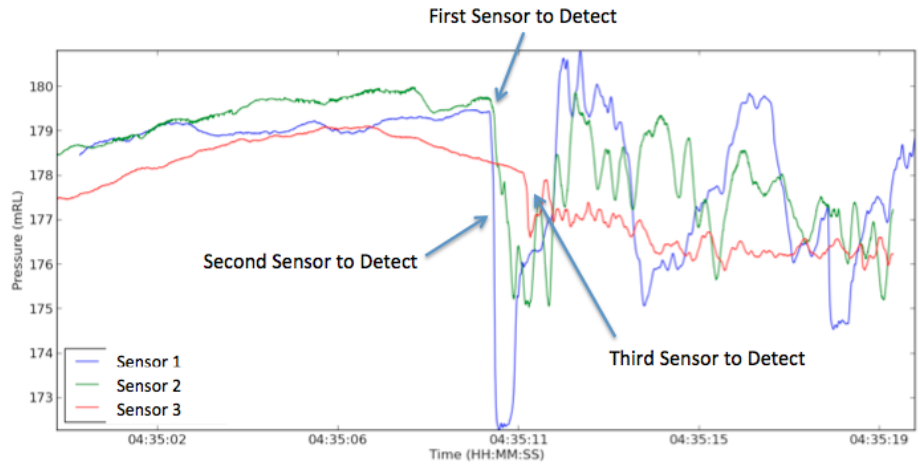
$$S_i = \sum_{\substack{j,k \in S_B \\ j \neq k}} |(t_j - t_k) - (\tau_{ij} - \tau_{ik})| \quad (2)$$

This metric combines the detection times from all the nodes that detected the event in the set S_B . In practice, the search space can be artificially limited as required, for example by providing a bound on the maximum distance a pressure transient is expected to travel in a network of a given complexity.

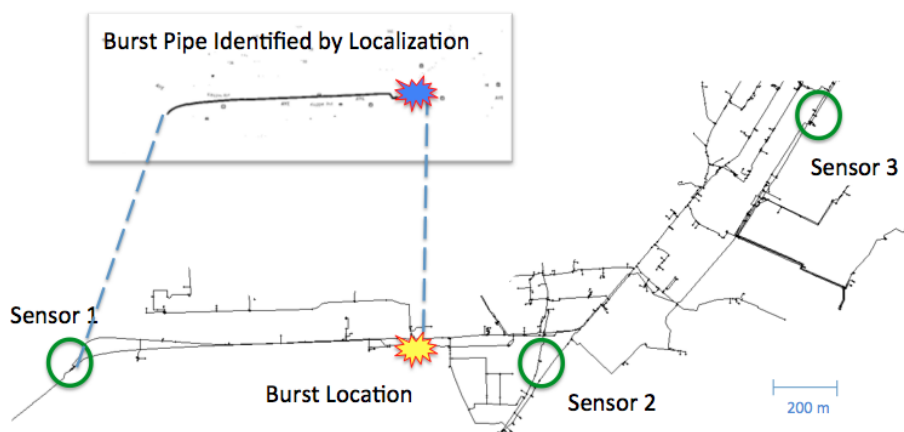
The most likely burst location is always quantized to the nearest junction, and this may not be the actual best match for the observed time of arrivals at each sensor node. Therefore, a second refinement step can be applied, where a local search is performed around the most likely vertex, by adding extra 'virtual' vertices in around it at fixed intervals along the edge (pipe). This allows accurate arrival times to provide accurate position estimates. In practice, the refinement step is not always needed, as it relies on very accurate detections of transients. The underlying algorithms for detection and localization have been validated through a series of controlled leak-off experiments, where burst events are created at fire hydrants using a solenoid valve. This approach led to an average localization accuracy of 37.5m over 9 trials on a 1km² section of pipe network (Fig. 4) (Srirangarajan et al. 2010).

Figure 5 shows an instance of a major pipe burst event (in a 700mm that was detected by three pressure sensors located 500m to 2000m from the source location. The event was detected automatically several hours before water was visible at the ground surface. Table 1 shows the Time Difference of Arrival (TDOA) estimates with respect to

Sensor 2 (the first sensor to detect the transient). These TDOA estimates are then used to localize this burst event. In this particular case, the localization process was able to identify the actual pipe where the leak had happened. More specifically, the vertex that was identified as the possible leak spot was only 1m away from the actual burst spot. Figure 5 shows the pipe identified by the localization process, which is a 700mm diameter pipe.



a) Pressures traces showing initial transient



b) Localization of burst event

Figure 5. - Detection of a major burst event (January 30, 20; sinkhole detected at 6:30am)

Table 1 – Time Difference of Arrival (TDOA) Estimates for Burst Event

TDOA	Sensor 1	Sensor 2	Sensor 3
Sensor 1: 4:35:10.398 am	0	0.110	-0.743
Sensor 2: 4:35:10.508 am	-0.110	0	-0.635
Sensor 3: 4:35:11.141 am	0.743	0.635	0

Very few methods for leak and burst localization have been proposed in the context of a large, looped network such as the FCPH network in Singapore. Many prior algorithms have validated using simulated data (Misiunas et al. 2003), in controlled laboratory environments (Stoianov et al. 2001, Misiunas et al. 2005), or in transmission pipelines that are immune from background pressure variations related to consumption (Misiunas 2005). Much of the complexity associated with the development of a reliable leak and burst detection system based around pressure transients is related to the dynamics of the real system.

DETECTING NON-BURST HYDRAULIC ANOMALIES

It is important to note that high-rate transients are a common occurrence in water distribution systems, and as such, not every transient event detected can be classified as a burst or leak event. For example, pumps operations can cause water hammer effects that result in large pressure transients.

WaterWiSe has amassed a large data archive of high rate, synchronized pressure data that has been mined to provide a library of characteristic events occurring in a system. This has allowed a coarse classification of transient profiles into broad categories.

Identifying leak hotspots and recurring events

Using the event detection and localization capabilities described in the previous section, it is possible not only to analyze abnormalities in real-time on sensor node data streams, but also to mine data from the archive of WaterWiSe data. This supports building a picture of characteristic transient signatures in the system with a view to classifying them with respect to severity (i.e., transients that are indicative of burst events are very important, while those associated with routine pumping or valve operations can be ignored). Figure 6 shows examples of different types of pressure transients that are observed in the network.

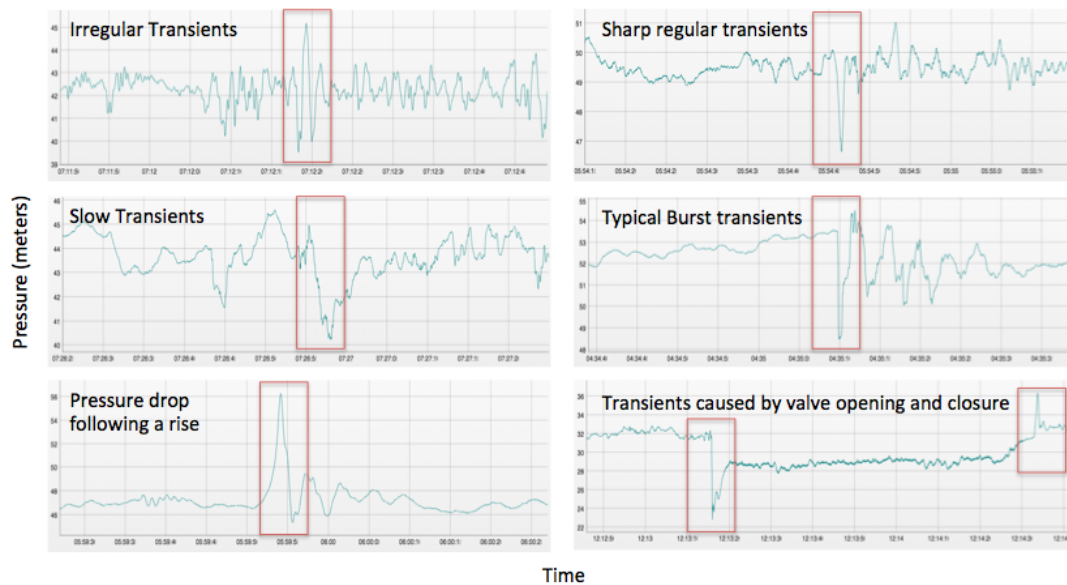


Figure 6. Examples of different transients detected using time-domain based statistical heuristics

The distinction between transients likely to be indicative of bursts vs. transients that are part of normal system operation is related not only to their signature, but also frequency of occurrence and location. The process of identifying critical transients is based upon the regular background transient level at each sensor location. The criticality in this case is a statistical measure that estimates the distance of the current transient under consideration from the rest of the transients that are regularly observed by a sensor (see previous Section on event detection heuristics).

In order to develop this analysis, events that are mined from the WaterWiSe archive are correlated across multiple nodes and localized (where possible), and the results aggregated onto a GiS map, along with known locations of consumers, or bulk meters. Events that are frequently detected, have similar characteristics, and localize to a known consumer can be discounted as normal behavior. Conversely, locations identified that do not appear to resolve to a known location of a consumer *and* happen infrequently may represent areas that require further investigation; these are known as *hotspots*. Figure 7 shows the data flow for identifying hotspots.

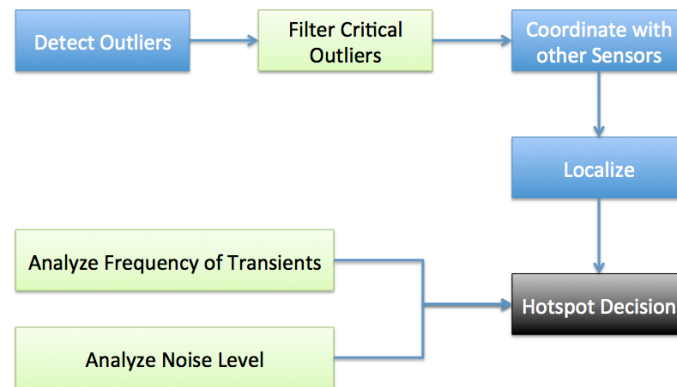


Figure 7. - Data flow for hotspot identification

Sometimes, the overall number of transients detected by a sensor may increase, indicating a possible major change in the water draw-off from the pipeline or gradually deteriorating condition of a pipe. Observing significant changes in the average number of transients detected by a sensor is also indicative of an on-set of anomalies such as pipe leaks. Figure 8 shows the number of transients detected per hour by two sensors. In one of the cases, number of transients detected at Sensor A rapidly increased one day before the actual burst happened. For Sensor B, the number increased gradually and was reported after being observed for two weeks. Field survey revealed large water draw-offs that were unknown to the utility. Thus, in both cases, monitoring the average daily total number of transients indicates the ability to provide early warning for bursts and detection of anomalous draw-offs.

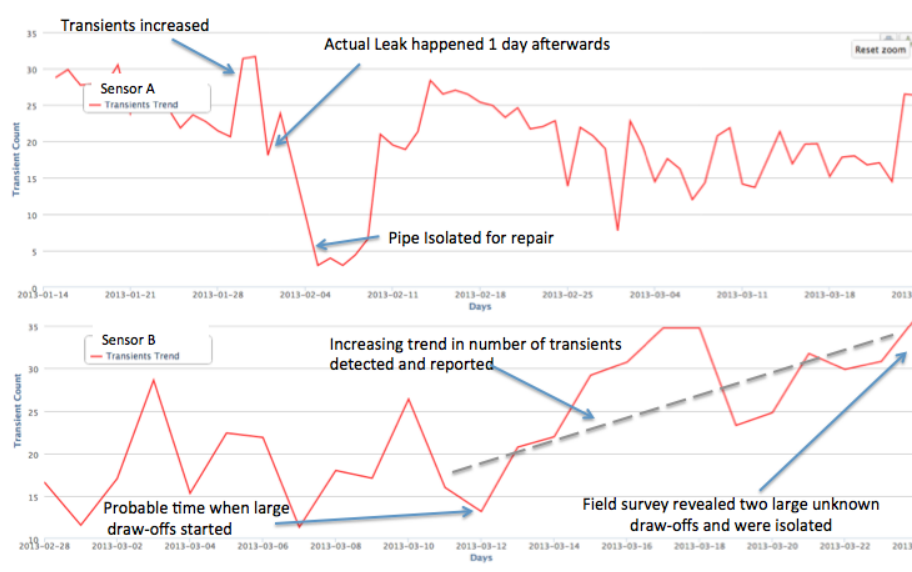


Figure 8. - Change in transient profile of a pipe can indicate onset of leaks.

A hot-spot analysis was conducted over a 12-month period for a commercial district in Singapore. Six sensors in this area were used to detect pressure transients, which were then localized to potential transient sources. During the period analysed, the network underwent some reconfigurations due to scheduled maintenance. These changes caused an increase in overall pressure baseline as well as an increase in the range of diurnal pressures. Most of the transient sources were localized to known bulk-meter locations (where regular pumping operations are used to fill roof-top storage tanks etc.). However, the analysis also identified three hot-spot areas that were traced to other undocumented changes associated with a construction site and a back-up site where potable water was used to flush the sewer system. The study showed the value of hotspot analysis with respect to understanding changes in hydraulic state within the system and locating other system anomalies.

FUTURE PLANS

The burst detection system described in the preceding section is now part of an operational online detection system that provides real-time notifications to the utility company. The research group is continuing to develop analytic

techniques for identifying the onset of slow leaks in the system. Other on-going research is focused on optimizing energy costs associated with pumping operations. The main challenge in this task is to integrate the sensor network with other sources of data (notably the automatic metering) and with scheduling of pump operations. Measurements of water quality have not been discussed in this paper. To date, the WaterWiSe system relies on conventional non-specific water quality measurands (pH, ORP, conductivity) whose baseline behavior depends on mixing of water from different sources and the age/residency time of water inside the distribution network. Using a well-calibrated hydraulic model, it is now possible to understand and detect water quality anomalies in the system using a variety of recently-developed multivariate time series tools (Hart et al. 2010, Perelman et al. 2012).

CONCLUSIONS

This paper has described WaterWiSe an integrated hardware and software platform combining a real-time wireless sensor network with intelligent analytics and modeling tools to better aid water distribution system operation and management. The system is built around a network of wireless sensor nodes that measure hydraulic and water quality parameters (including pressures at data rates $O[250\text{Hz}]$) within a large urban water distribution network in Singapore. Burst events are detected (at an individual node) from measurements of pressure transients using a combination of wavelet decomposition and time domain statistical analyses. Localization of the burst relies on accurate timing of transient wavefront arrivals and time synchronization of the nodes. A graph-based algorithm has successfully located the source used in controlled leak-off experiments (within a few tens of meters), and the system has also detected and localized several real burst events in near real-time (and in advance of damage observed at the ground surface).

The WaterWiSe pressure data archive has been used to characterize signatures of pressure transients from a range of normal recurring operations (routine pumping, valve operations etc.). By building a classification system of the transients, hydraulic anomalies (unusual signature from undocumented sources) are more readily identified and this offers a promising approach for remote detection of more slowly evolving events (slow leaks etc.).

The WaterWiSe monitoring system provides critical data within the distribution network that can enable optimization of pumping costs (while maintaining pressures and water quality). On-going research aims to develop more reliable understanding for detection of water quality anomalies.

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