

Toward An Integrated Approach to Localizing Failures in Community Water Networks (DEMO)

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Abstract—

We present a cyber-physical-human (CPHS) distributed computing framework, AquaSCALE, for gathering, analyzing and localizing anomalous operations of increasingly failure-prone community water services. Today, detection of water pipe leaks takes hours to days. AquaSCALE leverages dynamic data from multiple information sources including IoT (Internet of Things) sensing data, geophysical data, human input and simulation/modeling engines to create a sensor-simulation-data integration platform that can locate multiple simultaneous pipe failures at fine level of granularity with high level of accuracy and detection time reduced by orders of magnitude (from hours/days to minutes).

I. INTRODUCTION

Pipe leak is one of the most frequent types of failure in community water networks. Recent reports from Los Angeles Department of Water/Power (LADWP) and Washington Suburban Sanitary Commission (WSSC) indicate that communities are experiencing an unusual increase in pipe beaks, mainly in old pipes that are susceptible to corrosion problems and pipe joint displacements caused by surface deformations. Extreme weather and heavy rainfall (e.g. Hurricane Sandy 2012, El Niño 2016, La Niña 2017) can stress already weakened pipes to the point of causing major pipe breaks and significant increases in leak rates. Note that about 14-18% of water treated in the United States is wasted through damaged pipelines. Water quality can be compromised via contaminant propagation through a faulty pipe. A large-scale pipe failures or a pipe burst may cause flooding. Those failures in water infrastructure can have implications on other lifelines [1].

Present status of instrumentation: Water is relatively inexpensive resource. Consequently, most water networks are metered only for billing purposes. In the absence of any metering on water pipes, a utility can do little about leak localization except respond to customer complaints. Unlike above-ground structures where damage can be visibly seen, damage to underground pipes is often hidden. The only way to confirm break is to observe water that leaks to the surface.

Related localization approaches: One current practice is to use acoustic instruments listening for variation in the reflected signal, yet their effectiveness is only valid within an area around the leak and doing this is expensive [2]. Another approach adopted by utilities is to use hydraulic simulator to find a match between the simulation result and the meter data, but it is computationally expensive or prohibitive for large-scale water networks [3]. Several other techniques using fluid transient modeling, current-flow centrality, state estimation or machine learning (ML) have also been investigated. Their performance, however, are limited by specific contexts (e.g.

single leak, complete observation of the network, small and simple network topology).

To understand the operational performance and capture the dynamics of complex water networks, we argue that an integrated approach to fusing multiple (incomplete) sources of information is necessary. AquaSCALE is a computational framework that enables the fusion of diverse data sources, robust simulation engines and plug-and-play ML techniques. In the demonstration, we will show the difficulties of multi-leak localization and the detail of AquaSCALE workflow.

II. APPROACH AND SYSTEM OVERVIEW

AquaSCALE framework is a data-driven simulation engine. The input to the analyzer is derived from observations gathered from diverse data sources, and stored in the data management module. The analyzer subsumes models and techniques developed by domain experts and operates on live data to generate higher level awareness for specific application tasks (e.g. leak detection and flood prediction). The awareness then triggers corresponding logical adaptations within the framework (e.g. visualization tools for decision support, actuation and control of water infrastructures).

AquaSCALE is designed as a workflow based system comprised of multiple modules, as shown in Fig. 1. The **Scenario Generation Module** enables water managers and analysts to provide meaningful and diverse water contexts to the framework. A scenario is defined declaratively over user objectives, data sets, simulation and modeling engines, and model parameters. The **Sensor Data Acquisition Module** enables gathering of real-time field information for predefined scenarios by projecting the effects of new updates from the field on simulation outcomes. The **Integrated Simulation and Modeling Engine** executes hydraulic and hydrodynamic models to simulate the behavior of water networks and interactions between water infrastructures and floods. A **Plug and Play Analytics Module** is used to plug and unplug specific information, such as data sets and algorithms, at will depending on the specific context of applications, and to understand the advantage and limitation of diverse strategies in isolation and combination. Users/operators/analysts interact with AquaSCALE using the **Decision Support Module** to manage devices at runtime as they identify vulnerable spots and address accuracy/cost tradeoffs, and to optimize sensor placement for a better performance.

III. DEMONSTRATION

In the demonstration, we first run two failure scenarios as shown in Fig. 2 to illustrate that compared with single-

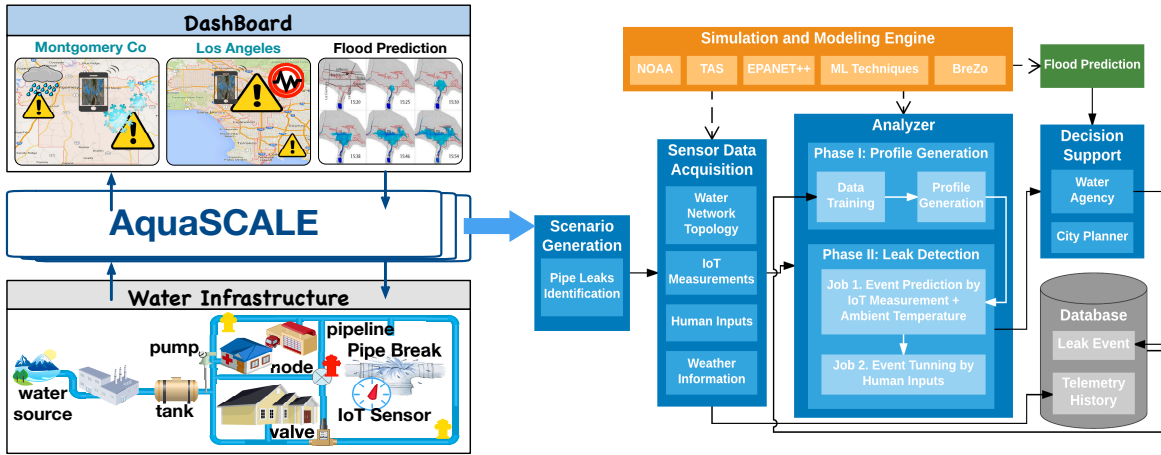


Fig. 1: AquaSCALE prototype initial implementation. AquaSCALE enables the identification of anomalous events at two layers, a higher service layer that determines water service availability and a lower layer that determines built infrastructure availability, via information integration and plug-and-play capability.

leak, multi-leak event become much more complex to detect and locate. By executing EPANET++, an enhanced version of a commercial grade hydraulic simulator EPANET [4], with a sample network, the demo shows that multiple leak events interact with each other and jointly affect the hydraulic behavior, making it difficult to extract correct message in a timely manner.

We then present the detail of AquaSCALE for multi-leak identifications. By following the workflow in Fig. 1, we start with scenario generation by defining a multi-leak identification problem. We use a real-world subzone water network provided by WSSC and collect information from multiple sources - EPANET++, TAS (Twitter Acquisition System [5]) and NOAA (National Oceanic and Atmospheric Administration). EPANET++ allows to model community water distribution systems and enables the modeling of sensor devices and pipe leaks. The input to the analyzer is derived from observations including water network topology, pressure heads, flow rates, human reports and ambient temperatures that are stored in the data management module. To detect and localize leak events, we plug and play a variety of Machine Learning (ML) based techniques over gathered information using Python scikit-learn. We show a two-phase approach where the profile model is generated offline by learning an extensive amount of measurements in water infrastructures (Phase I) and the human and temperature data is aggregated with predicted results from the profile model when live data coming in (Phase II). To study the propagation and cascading effects of pipe failures, we utilize BreZo, a hydrodynamic flood model, to execute dynamic simulation of flood events by modeling flood depths, flooded maps and flow velocity that are essential for improved flood warnings.

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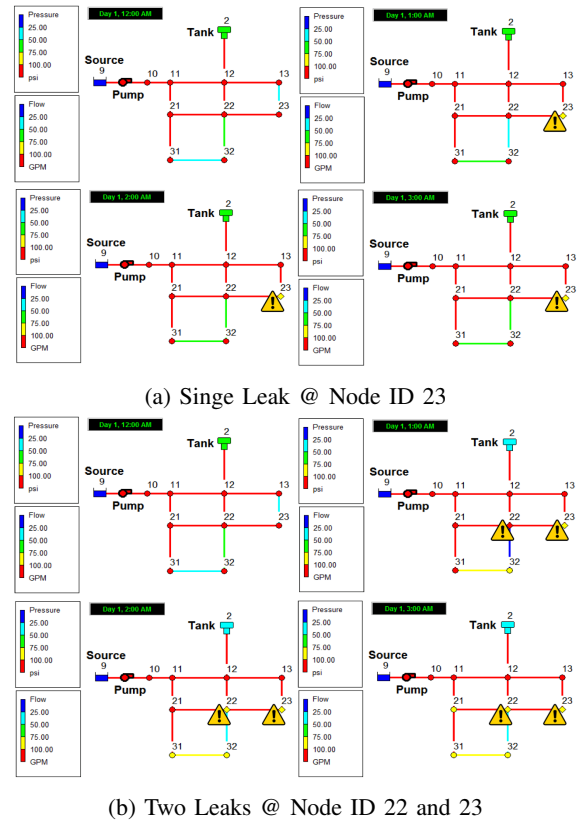


Fig. 2: Changes on hydraulic behaviors along with the time caused by (a) single and (b) multiple leaks.

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