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Robust sensor placement for pipeline monitoring: Mixed integer and greedy optimization

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ABSTRACT

Intelligent water systems – aided by sensing technologies – have been identified as an important mechanism towards ensuring the resilience of urban systems. In this work, we study the problem of sensor placement that is robust to intermittent failures of sensors, i.e. *sensor interruptions*. We propose robust mixed integer optimization (RMIO) and robust greedy approximation (RGA) solution approaches. The underlying idea of both approaches is to promote solutions that achieve multiple detectability of events, such that these events remain detectable even when some sensors are interrupted. Additionally, we apply a previously proposed greedy approximation approach for solving the robust submodular function optimization (RSFO) problem. We compare scalability of these approaches and the quality of the solutions using a set of real water-networks. Our results demonstrate that considering sensor interruptions in the design stage improves sensor network performance. Importantly, we find that although the detection performances of RMIO and RGA approaches are comparable, RMIO generally has better performance than RGA, and is scalable to large-scale networks. Furthermore, the results demonstrate that RMIO and RGA approaches tend to outperform the RSFO approach.

1. Introduction

In recent years, there have been rapid developments in wireless sensor-grids for intelligent systems in the urban environment, such as monitoring air quality [29], stormwater collection [18] and water supply systems [26]. In the urban water supply, motivating examples of intelligent systems include the PipeNet@Boston [43], WaterWise@ Singapore [2], and SWND@Bristol [47]. Such deployments enable the implementation of sensing technologies and improve water management by monitoring pressure and water quality, and detecting pipe failures and leakages [1]. These intelligent systems integrate a physical water-network and a cyber sensor-grid, and extend the capabilities of traditional supervisory control and data acquisition (SCADA) systems by providing real-time information at a fine spatial-temporal resolution that was previously unavailable.

The sensor placement problem can be generally stated as finding the optimal sensor locations such that network observability (or event detectability) is maximized given a limited number of sensors. The sensor placement problem is not unique to the water sector and can be found in many engineering applications [24,20,22]. In the context of urban water networks, the sensor placement problem has been well-studied for detecting contamination events, starting from the early warning event detection systems [23,19] to the more recent applications for monitoring water quality [50]. Several impact measures have been suggested to assess the functionality of a sensor-grid including detection likelihood, time to detection, volume of contaminated water, and affected population [34]. The underlying assumption of the impact measures is that with increased functionality of the sensor-grid there is improved functionality of the water-network. The uncertainty of contamination events is typically quantified by assuming that the stochastic events occur with given probabilities, which are used to generate a subset of contamination scenarios. The optimization problem is then solved by minimizing the impact of the sampled contamination scenarios. While the majority of researchers have considered minimizing the average impact of contamination scenarios, additional performance measures have been suggested including value at risk, tail-conditional expectation, and worst-case events [35,37]. These measures consider the impacts of the worst-case events and reduce the number of high-impact contamination events [45]. For a detailed review of sensor placement for water quality and contamination event detection in water networks, see [16,38].

Despite the extensive literature, the application of continuous monitoring of water quality within water distribution systems has been extremely limited in practice due to high investment, operations and

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management costs, and low level of reliability of the generated data [1]. In light of the real-applications mentioned previously [43,2,47], recent works have focused on monitoring pressure for burst and leakage detection [12,40,26,49]. Several model-driven approaches have been suggested for leak detection and localization in water-networks. Model-based leak detection methods have relied on a sensor-grid continuously collecting and transmitting observations, such as pressure and flow, and have compared these observations with the expected values [31,36]. In the context of the sensor placement problem, some recent studies have considered both model-based and distance-based sensing functions to detect pipe bursts and leakage events [12,39,30,40].

Various solution approaches have been suggested for the sensor placement problem. These can be classified into: (1) mixed integer optimization (MIO), in which the problem is formulated similar to facility location or maximum covering set problems; this approach takes advantage of efficient solution schemes for solving large-scale MIO problems [6], (2) greedy approximations (GA), which utilize the properties of submodular functions leading to solutions with approximation guarantees [21], (3) evolutionary algorithms, in which the solution approach relies on heuristic search techniques and the integration of hydraulic simulations with optimization algorithms [33,14], and (4) complex network approaches, which rely on network topology and centrality measures to suggest potential sensor locations [48,13].

The majority of previous works have treated the sensor placement problem as deterministic, in which all sensors are perfectly operational. As modern solution approaches can successfully solve the deterministic sensor placement problem for very large water networks [6,21,40], several recent studies have suggested modeling more realistic assumptions, such as imperfect sensors [5], data uncertainties [9], and high-consequence contamination events [45]. In Watson et al.[45], the problem of robust sensor placement is addressed by maximizing the worst-case detection performance (instead of the average case) against a set of possible contamination scenarios. The problem is formulated as a MIO and a few heuristics are applied to reduce the size and complexity of the straightforward formulation. In Carr et al. [9], the robustness of the design has been modeled by treating the impacts of the contamination events in the objective function as uncertain. Several robust MIO-based formulations and linear relaxations are developed and compared. In Krause et al. [21], a general purpose greedy algorithm has been suggested, which approximately solves robust submodular problems by introducing a truncated objective function. Both data uncertainties and sensor failures can be modeled under this solution approach. Results demonstrate comparable performance to greedy optimization without considering sensor failures. The problem studied by Orlin et al. [32] considers robust monotone submodular function optimization (RSFO) against the worst-case sensor failures. Orlin et al. [32] introduce several constant factor approximation algorithms, which are greedy in nature, to find a sensor placement that is robust against single and multiple failures of sensors. In Section 2.4, we instantiate the RSFO approach so that it can be directly compared against the approaches introduced in this work.

Our main motivation is to consider uncertainty in the functioning of the sensors when selecting sensor locations. This work is driven by real sensor deployments [29,43], which report that sensors need to be periodically disconnected from the grid due to routine maintenance operations (e.g. battery replacement and calibration), malfunctioning (e.g. manufacturer flaws), or random failures (e.g. communication disruptions). Regardless of the reason of the failure, our goal is to ensure a desired level of functionality of the remaining operating sensors. Specifically, we are interested in solving the sensor placement problem that *maximizes the number of detectable events and is robust to the interruption of sensors.* The underlying idea of our approach is to promote solutions that achieve multiple event coverage, such that these events remain detectable even when some sensors are taken off-line.

In general, there are two pre-dominant approaches to handle uncertainty in the optimization problems: stochastic and robust. Stochastic approaches require knowing the probability density functions of the uncertain data. However, the size of the optimization problem can increase significantly, since the uncertainty is often assimilated through a large number of sampled scenarios [41]. Robust approaches focus on formulating a deterministic equivalent of the uncertain problem, and seek an optimal solution that is robust to all uncertain scenarios. In other words, the robust approach optimizes against the *worst-case* scenario. This representation does not require knowing the full distribution of the uncertain variables and is tractable, i.e. the uncertain optimization problem is approximately the same size as the original deterministic model. This form of worst-case analysis has been widely studied as *robust optimization* in operation research [3,7]. The modeling approach suggested in this work considers the worst-case viewpoint. Adopting the ideas from robust optimization, we propose robust mixed integer optimization (RMIO) and robust greedy approximation (RGA) extensions of the sensor placement problem. In these formulations, some of the events remain detectable even if the detecting sensors are temporarily off-line, resulting in a solution that is robust to sensor interruptions.

In particular, we study the scalability of the RMIO formulation, which takes advantage of advances in modern MIO solvers and hardware speedup [8], and investigate its solution quality compared to the RGA. We assess the performance of the solution approaches through a set of real water-networks of various sizes. Furthermore, we evaluate the performance of the greedy approximation algorithm for solving the RSFO, as previously introduced by Orlin et al. [32]. We show, through extensive simulation experiments, that RMIO and RGA approaches, suggested in this work, generally outperform the RSFO approach. Note that our formulation is related to previous work in sensor placement problems with a limited budget [6,21], however, in our setting, the operation of sensors can be interrupted.

To better understand our basic setup, consider the illustrative network shown in Fig. 1. Here, the problem is to detect pipe bursts by sensing the pressure at network nodes. There is a total of 6 pipes, i.e. 6 potential pipe burst events. Sensor locations are represented by the shaded nodes and each sensor can detect failures of adjacent pipes (shown by the thick black lines). Consider cases (a) and (b) (see Fig. 1), in which, given two sensors, five events can be detected. If one sensor is interrupted, then in the worst-case, only two events remain detectable in case (a) (sensor 2 is off-line), compared to three events in case (b) (sensor 2 is off-line). Our approach suggests placing sensors such that as many events as possible remain detectable when some sensors are disconnected from the grid, i.e. promoting case (b).

The paper is structured as follows. In Section 2.1, we review the formulation of the fault detection matrix for the sensor placement problem. In Section 2.2, we formulate the robust mixed integer optimization solution approach, and in Section 2.3, we briefly discuss the robust greedy approximation approach for the robust sensor placement problem. In Section 2.4, we introduce the RSFO solution approach and its application to robust sensor placement. In Section 3, we evaluate the performance of the three solution approaches and report our key results. Finally, Section 4 contains some concluding remarks and future directions.

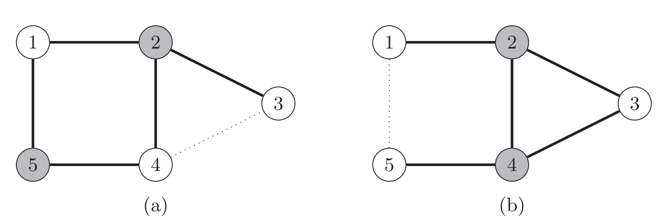

Fig. 1. Example network. The sensor's locations are represented by the shaded nodes and the covered pipes by the thick black lines: (a) Optimal coverage = 5, Worst coverage (*sensor 2 off-line*) = 2; (b) Optimal coverage = 5, Worst coverage (*sensor 2 off-line*) = 3.