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Advancing Water Distribution Network Calibration: A Framework for Comparing Static and Mobile Sensing Approaches †

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Abstract: This study introduces a novel framework for conducting a comparative analysis of static and mobile sensing approaches for the collection of data to be used in network calibration. Two new algorithms that optimize deployment for both static and mobile sensors are proposed. The results indicate that deploying a single mobile sensor starting from various locations throughout the network for 24 h can yield pipe roughness calibration results as good as, or slightly superior, to those obtained using static sensors at approximately 90% of the potential monitoring nodes.

Keywords: static sensing; mobile sensing; water distribution network; calibration; optimization

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1. Introduction

Conventionally, static sensors are deployed "strategically" for the continuous monitoring of pressure, flow, and water quality for leak detection, identifying contamination, and calibrating hydraulic network models [1,2]. However, emerging mobile sensor technology introduces a novel opportunity offering more flexibility and the collection of potentially more valuable data [3]. The efficiency or improvement possible is currently unknown. This study introduces a framework for the comparative analysis of static and mobile sensing methods for hydraulic network model calibration. This paper presents new algorithms that optimize deployment for both static and mobile sensors, enhancing precision for network-wide pipe roughness calibration. We assessed the calibration quality of the two approaches (static and mobile) using a benchmark network, where the original network's pipe roughness served as the 'ground truth'.

2. Material and Methods

The static method optimizes sensor placement and numbers for continuous data collection. In contrast, the mobile approach uses a moving sensor with its position based on speed, pathway, and the duration of deployment. The mobile method optimizes for location and time of release, speed of travel, and the path taken by the mobile sensor (the robot). In both static and mobile-sensing methodologies, the calibration of pipe roughness and the placement of sensors or mobile sensor properties are tackled through the formulation of two consistent (between mobile and fixed strategies) objective optimization problems implemented in C++.

The first objective is to minimize the calibration performance residual, reflecting disparities between the measured and computed pressure head. The secondary objective aims to maximize knowledge derived from sensor measurements and sensor coverage within the network. To accomplish this, a weighting factor is introduced to balance the optimization between knowledge maximization and sensor coverage. The objective functions are defined as follows:

$$Minimise\ f_1^s = \sum_{t=1}^{T}\sum_{n=1}^{N}\left(H_{meas}(t,n) - H_{comp}(t,n)\right)^2 \tag{1}$$

$$Maximise\ f_2^s = \left[\alpha * \left(\frac{N_s}{N_p}\right) + (1-\alpha) * \left(\frac{S_s^2}{\sigma^2}\right)\right] \tag{2}$$

$$Minimise\ f_1^m = \sum_{t=1}^{T}\left(H_{meas}(t,x(t),y(t)) - H_{comp}(t,x(t),\ y(t))\right)^2 \tag{3}$$

$$Maximise\ f_2^m = \left[\alpha * \left(\frac{N_{vl}}{N_L}\right) + (1-\alpha) * \left(\frac{S_m^2}{\sigma^2}\right)\right] \tag{4}$$

where f_1^s, f_2^s, f_1^m, and f_2^m denote objective functions for static and mobile sensing. $H_{meas}(t,n)$ and $H_{comp}(t,n)$ represent the measured and computed head at time t and node n for static sensing. $H_{meas}(t,x(t),y(t))$ and $H_{comp}(t,x(t),y(t))$ represent the measured and computed head at time t for a mobile sensor at pipe network position $(x(t),y(t))$. N_s and N_p are the number of static sensors and potential locations, respectively. N_{vl} and N_L signify links visited by the mobile sensor and total links. S_s^2 and S_m^2 represent the variance in observed head values for static and mobile sensing, respectively, while σ^2 denotes the total network-wide observed head variance. α is a weighting factor. f_1^s and f_1^m are normalized by the total measured head values. Each network node can serve as both a potential static sensor location and a potential mobile sensor release point. The methods employ NSGA II for optimization and EPANET for network performance evaluation.

3. Results and Discussion

The methodology was applied to a fully looped network comprising 24 nodes and 34 pipes, where two reservoirs maintain fixed water levels at 100 m and 95 m, respectively [4]. Figure 1 displays the network layout. The optimization process includes a 24 h simulation with hourly hydraulic time steps to accommodate demand fluctuation. The number of candidate pipe roughness values used was 16, ranging from 0.045 to 6.77 mm. It is important to note that the values of t referred to in Equations (1) and (3) were the same for static and mobile approach evaluations.

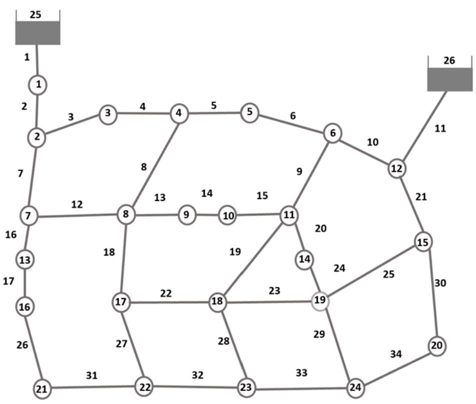

Figure 1. Network layout showing node and pipe references.

For mobile sensing, we employed a single moving sensor with 16 sensor speeds ranging from 0.3 to 1.8 m/s, in addition to 32 randomly generated paths. Crossover and mutation probabilities were set to 1.0 and 0.005, respectively. The optimization process iterates through 5000 generations with a population size of 100. Optimization is conducted across five weighting factor values (α) to generate trade-off curves for the two objective functions. Figures 2 and 3 depict the Pareto fronts for static and mobile sensing approaches across different α values. For mobile sensing, these fronts depict scenarios where the mobile sensor is released from Node 1. It can be observed that varying α influences the optimization process, particularly with α set to 0.9, where a significant concentration of solutions is observed towards higher values of the f_2 objective function. Additionally, increasing α enhances the visibility of knee points on the Pareto front—signifying significant trade-off changes between the two objectives.

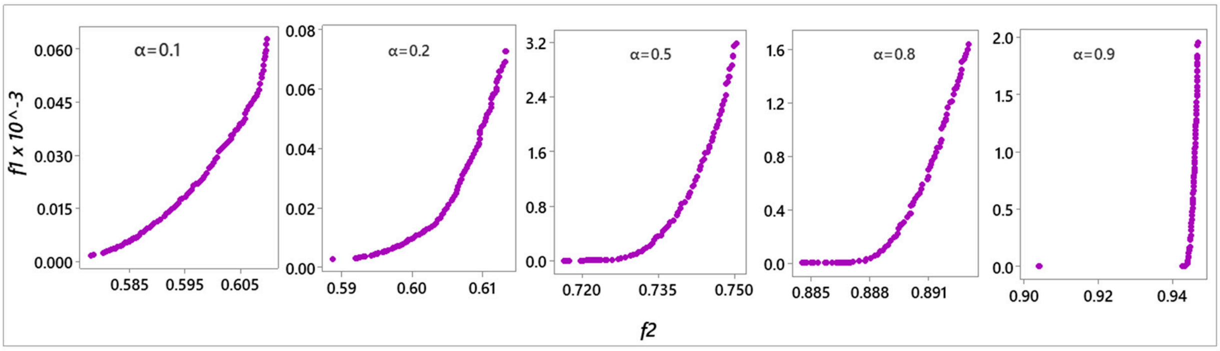

Figure 2. Pareto front for different α values for the static sensor approach.

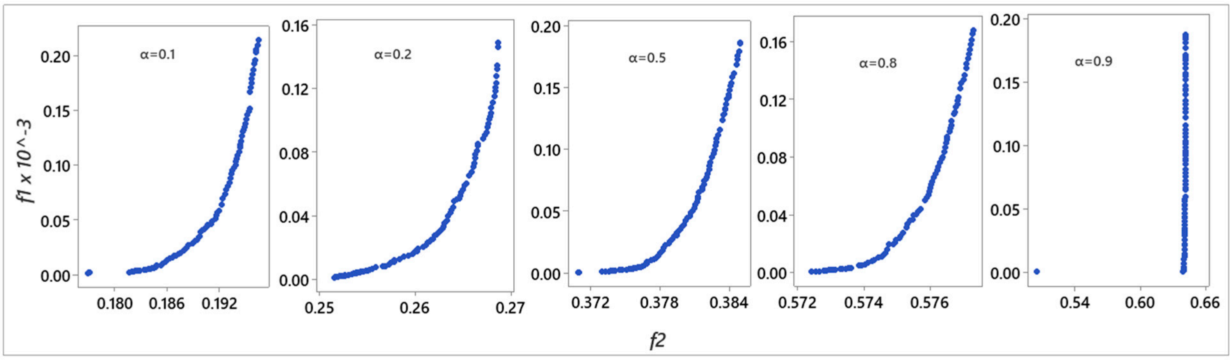

Figure 3. Pareto front for different α values for a mobile sensor released from Node 1.

The quality of the solutions along the different Pareto fronts was assessed using the metrics of the Mean Absolute Error (MAE) and the standard deviation of the pipe roughness error. As detailed in Table 1, among the static sensing approaches, α = 0.2 appears as the top-performing weighting factor, yielding an MAE of 1.06 mm and a standard deviation of 2.02 mm, which was achieved with a deployment of 21 static sensors. Conversely, in mobile sensing scenarios, α = 0.8 demonstrates superior performance, attaining an MAE of 1.05 mm and a standard deviation of 1.90 mm, coupled with an optimal speed of 0.9 m/s, using only one sensor. While α = 0.8 yields the optimal results, it is noteworthy that α = 0.1 and 0.2 demonstrate comparable performance.

Table 1. Comparison of optimal results obtained from static and mobile sensing approaches.

α	**0.1**	**0.2**	**0.5**	**0.8**	**0.9**
Static sensing approach					
Mean Absolute Error of pipe roughness (mm)	1.55	1.06	1.24	1.32	1.35
Standard deviation of pipe roughness error (mm)	2.59	2.02	2.40	2.40	2.46
Optimal number of static sensors	16	21	23	24	24
Mobile sensing approach [1]					
Mean Absolute Error of pipe roughness (mm)	1.10	1.13	1.27	1.05	1.37
Standard deviation of pipe roughness error (mm)	1.97	1.99	2.26	1.90	2.49
Optimal sensor speed (m/s)	1.5	0.3	0.9	0.9	1.0

[1] Mobile sensor released from Node 1.

The mobile sensing approach was further evaluated using weighting factors $\alpha = 0.2$ and $\alpha = 0.8$ across various sensor release nodes (e.g., Node8, Node12, Node19, Node21, Node24) representing physically diverse positions within the network. Among the re-lease nodes, Node12 showed superior performance with an MAE of 0.68 mm and a standard deviation of 1.11 mm for $\alpha = 0.2$, while Node8 performed comparably to Node1 for $\alpha = 0.8$ with an MAE of 0.97 mm and a standard deviation of 1.94 mm. The release Nodes 8 and 12 had optimal sensor speeds of 1.1 m/s and 1.8 m/s, respectively.

Upon comparing the optimal outcomes achieved through mobile and static sensing, it was observed that a single mobile sensor yielded results as good as or slightly better than those obtained with static sensors across 23 out of the 24 potential monitoring nodes.

4. Conclusions

Our study presents a new framework for conducting a comparative analysis of static and mobile sensing methods for hydraulic network model calibration. Our findings indicate that a single mobile sensor, active within the network for 24 h, can achieve results comparable to or better than a considerably large number of fixed, continuous sensors strategically placed at various monitoring nodes. In terms of data efficiency, the static sensors yielded a total of 504 data points (21 sensors $\times$ 24 h), while the mobile sensor provided 24 data points (1 sensor $\times$ 24 h). Despite collecting fewer data points, the mobile sensor still delivered comparable results. While this was only shown for a relatively small but heavily looped network, it suggests that mobile sensors have the potential to transform the calibration of data collection for accurate hydraulic network modeling.

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