Hybrid Mobile-Stationary Urban Sensing

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***Abstract*—Urban environmental monitoring in smart cities requires a balance between spatial coverage, accuracy, and operational costs. Traditional fixed sensor networks are often too expensive to deploy at high density, resulting in sparse coverage that misses localized patterns. While opportunistic mobile sensing using service fleets (e.g., waste collection trucks) offers a cost-effective alternative, it is constrained by predefined routes and irregular sampling, resulting in spatial and temporal blind spots. This work proposes a hybrid sensing framework that integrates mobile fleets with strategically placed fixed sensors to ensure adequate spatio-temporal observability.**

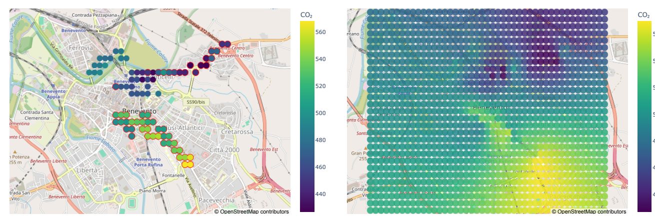
***Index Terms*—mobile urban monitoring, fleet management, interpolation, spatio-temporal observability, stationary sensors.**

I. Introduction

Traditional urban monitoring relies on fixed stations that, while accurate, are costly to install and maintain, often resulting in sparse spatial coverage that misses fine-grained pollutant gradients. In complex urban environments, parameters like CO_2 can vary substantially over short distances (< 1 km) due to traffic and local emissions [1]. To address this, municipalities are increasingly adopting mobile sensing platforms. However, mobile sensing introduces significant challenges, as service vehicles follow strict operational schedules, leading to non-uniform sampling in which main roads are over-sampled while peripheral zones remain unobserved. Furthermore, the lack of data continuity across time makes accurate data reconstruction difficult. Interpolation techniques can help mitigate these issues. Temporal interpolation can be used to reconstruct missing observations when past measurements are available. As illustrated in Fig. 1a, markers with a red border represent values temporally reconstructed using the PCHIP. Temporal interpolation can then be complemented by spatial interpolation methods, exploiting well-established techniques, such as RBF, as shown in Fig. 1b.

However, there is a critical need for a systematic methodology that not only interpolates sparse data but also evaluates how effectively a fleet observes the environment. This abstract addresses this gap by providing an Edge-Fog-Cloud framework designed to optimize hybrid infrastructures. By combining "what-if" analysis with greedy optimization, the system can autonomously recommend which vehicles to instrument and where to deploy fixed sensors to bridge coverage gaps [2].

This work is framed within the topics of the TRUST (urban monitoring infrastructure and dynamic fleet management to support the implementation of the TARIP) research project.



(a) Spatio-temporal augmented cells. (b) Complete Mesh.

Fig. 1: Spatio-temporal interpolation phases.

II. Methodology and Observability Metrics

The framework discretizes the urban area into regular grid cells (e.g., 100m x 100m) $\mathcal{C} = \overline{Lat} \times \overline{Lon} = \{c_1, \ldots, c_N\}$ and fixed temporal windows $\mathcal{T} = \{t_1, \ldots, t_T\}$ to perform a unified analysis of sampling density. Some metrics are introduced to quantify the sensing informative capability:

- Temporal Observability Index (TOI): Measures the fraction of time slots during which a specific cell is monitored, identifying persistent "blind spots". Given the set of all samples $\mathcal{D} = \{d_1, ..., d_K\}$ the metric is defined as:
$$\text{TOI}(c_i) = \frac{1}{|\mathcal{T}|} \sum_{t_r \in \mathcal{T}} \mathbf{1}\left[\exists\, \overline{d_j} \in \overline{\mathcal{D}} : c_j = c_i \wedge t_j = t_r\right] \tag{1}$$
where $\mathbf{1}[\cdot]$ is the indicator function, equal to 1 if the condition holds and 0 otherwise.
- Value of Fleet (VoF): Quantifies the relative variation in RMSPE of a fleet configuration $E_{\mathcal{F}_c}$ with respect to a baseline configuration E_{baseline}. Higher VoF values correspond to larger reconstruction errors relative to the baseline
$$\text{VoF}(c) = \frac{E_{\mathcal{F}_c} - E_{\text{baseline}}}{E_{\text{baseline}}}. \tag{2}$$
- Fleet Information Efficiency (FIE): Evaluates the information yield per unit of operational cost (depreciation, fuel, and labor), identifying the fleet configuration $\mathcal{F}_c$ that minimizes interpolation error (RMSPE) $E_{\mathcal{F}_c}$ without a proportional increase in expenses $C_{\mathcal{F}_c}$
$$\text{FIE(c)} = \frac{E_{\mathcal{F}_c}}{C_{\mathcal{F}_c}}. \tag{3}$$

The cost of the fleet configuration can be calculated as:

$$C_{\mathcal{F}_c} = \alpha\,|\mathcal{F}_c| \;+\; \beta\,L_c \;+\; \gamma\,T_c \tag{4}$$

where $|\mathcal{F}_c|$ denotes the number of vehicles, L_c the total traveled distance, and T_c the overall operation time. The weighting factors α, β, and γ model vehicle-related costs, distance-dependent expenses (e.g., fuel consumption), and operation-time costs (e.g., personnel salary).

The proposed metrics serve as evaluation indicators and as decision-support tools. Through a set of what-if analyses, they enable the assessment of alternative deployment strategies and support the generation of actionable recommendations for fleet configuration and sensor placement.

III. Actionable Recommendations for Infrastructure Co-Design

The methodology was validated using a real-world dataset of CO_2, temperature, and humidity collected in Benevento, Italy. The framework generates data-driven suggestions to autonomously adjust physical configurations:

A. Optimizing Mobile Fleet Selection

Through a systematic what-if analysis, the system evaluates different fleet sizes and routing patterns. The cases considered are summarized in Table I. For each case, we indicate whether the Node is chosen as an oracle ("O") or as a sampling vehicle ("S"). The first case represents the baseline.

TABLE I: Fleet resizing considered cases.

	Fleet configuration (c)	Node 1	Node 2	Node 3
2 Vehicles	1 (baseline)	S	S	O
	2	S	O	S
	3	O	S	S
1 Vehicle	4	S	O	O
	5	O	S	O
	6	O	O	S

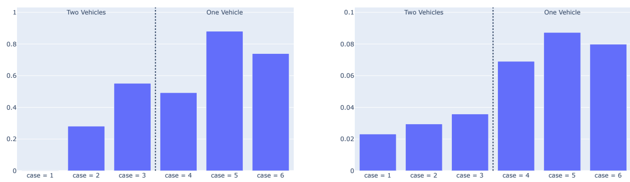
For each configuration, we evaluated the VoF metric using Eq. (2). Lower values indicate a closer match to the baseline and correspond to the configuration with the lowest error. Results are presented in Figure 2a. The best configurations are 1 and 4 for two- and one-vehicle fleets, respectively.

To evaluate FIE, the trajectory costs for each considered vehicle are summarized in Table II.

TABLE II: Trajectories costs.

Trajectories			Costs			
Vehicle	Distance [km]	Time [h]	Fixed $\alpha = 60$	Distance $\beta = 0.25$	Time $\gamma = 60.76$	Total
Node 1	28.725	1.21	60	7.18	73.52	140.70
Node 2	16.757	1.25	60	4.19	75.95	140.14
Node 3	22.729	1.25	60	5.68	75.95	141.63

Applying the FIE in Eq.(3) yields the results reported in Figure 2b. Lower FIE values indicate more favorable trade-offs between interpolation error and operational cost. Results confirm configuration 1 and 4 as the best compromise.



(a) Value of Fleet, VoF
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(b) Fleet Information Efficiency, FIE.

Fig. 2: Fleet Indicators in fleet resizing scenarios.

B. Greedy Placement of Fixed Sensors

To mitigate gaps where mobile coverage is persistently low (low TOI), the framework employs a greedy maximization strategy. It first applies an isotropic convolution kernel to the TOI map to identify spatially coherent coverage gaps (areas where sensing is consistently absent). It then uses a Euclidean distance transform to iteratively select fixed sensor positions, ensuring that new sensors are placed far from existing coverage and maximizing global spatial diversity. The greedy algorithm identified five optimal sensor locations, which, once installed, would provide constant temporal coverage (TOI = 1) in previously unobservable zones, as shown in Fig.3.

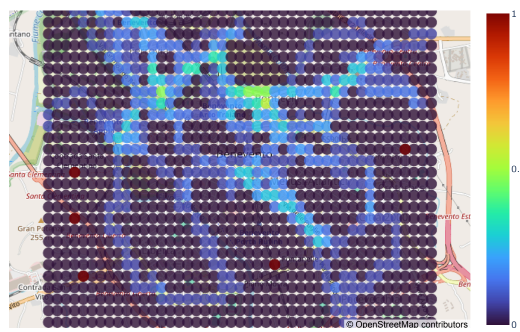

Fig. 3: Greedy placement of fixed sensors.

IV. Conclusion

This work provides a reusable toolkit for municipalities to transition from static, sparse monitoring to adaptive, hybrid sensing infrastructures. By linking operational costs directly to observability metrics, the framework ensures that urban sensing is both effective and economically sustainable.

The results identified "Case 4" (using only Vehicle 1) as the most efficient single-vehicle configuration, offering the best compromise between monitoring performance (lower RMSPE) and operational simplicity, and the greedy algorithm identified the optimal sensor locations for fixed monitoring stations.

References

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