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Research Title

Reinforcement Learning-Based Sensor Deployment for Urban Micro-Network $PM_{2.5}$ Mapping: A Case Study of Dhaka

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1. Abstract

Air quality management in Dhaka is constrained by the lack of dense ground-based monitoring, despite the city being consistently ranked among the most polluted worldwide. Accurate mapping of fine particulate matter ($PM_{2.5}$) is essential for exposure assessment, public health, and regulatory planning. However, large-scale deployment of monitoring devices is limited by financial and operational challenges. Existing approaches such as Gaussian Processes, clustering methods, and variance reduction heuristics have demonstrated effectiveness, but they remain insufficient in Dhaka's heterogeneous and dynamic environment. In this study, we propose a reinforcement learning (RL) based framework for the deployment of low-cost micro-network sensors. By training RL agents on fused datasets, the objective is to minimize spatial reconstruction error while prioritizing coverage in vulnerable neighborhoods. The framework will be benchmarked against traditional siting methods and validated using real-world data, addressing a key gap in urban monitoring and showing the potential of RL for environmental resilience.

2. Introduction

Dhaka is one of the most polluted megacities in the world, with annual mean $PM_{2.5}$ concentrations frequently exceeding 70 $\mu g/m^3$, far above the World Health Organization (WHO) guideline value of 5 $\mu g/m^3$ [1], [2]. The current monitoring infrastructure, including Continuous Air Monitoring Stations (CAMS), provides only sparse coverage and fails to capture the sharp local variations caused by traffic emissions, brick kilns, industrial clusters, and seasonal meteorological influences [3]. Although satellite-derived Aerosol Optical Depth (AOD) combined with data fusion techniques has been employed for air quality estimation, these methods depend strongly on reliable ground-based measurements for calibration and validation, which are still limited in Dhaka [4].

Low-cost sensor networks are widely recognized as a scalable alternative, but financial and logistical constraints prevent their city-wide deployment, making optimized placement strategies essential. Traditional approaches such as Gaussian Process variance reduction [5], clustering algorithms, and static optimization [6] provide useful insights, but they face three major challenges: (i) They typically treat sensor placement as a one-time decision rather than a sequential process, (ii) They do not adequately account for multiple objectives such as equity and deployment cost, and (iii) They show limited scalability in complex urban environments. Reinforcement learning (RL) offers a promising alternative by enabling adaptive and sequential decision-making for siting policies that can respond dynamically to uncertainty and evolving conditions [7].

3. Research Questions

1. Can Reinforcement Learning (RL) be effectively used to learn optimal deployment strategies for low-cost air quality sensor micro-networks in Dhaka?
2. How does RL-based deployment compare against baseline methods such as greedy variance reduction, Gaussian Processes, and clustering-based placement?
3. To what extent can RL deployment policies account for spatial heterogeneity, equity in coverage, and practical feasibility in dense urban environments?

4. Literature Review

Research on air quality mapping and sensor deployment has grown rapidly over the past decade. Multiple studies have documented spatiotemporal variation of $PM_{2.5}$ in Bangladesh. Islam et al. [3] reported that meteorological conditions strongly influence $PM_{2.5}$ and PM_{10} across major cities, while localized measurements from Dhaka's Export Processing Zone provided high-resolution datasets of $PM_{2.5}$, PM_{10}, and CO for model calibration [8]. Additional studies identified persistent $PM_{2.5}$ hotspots in and around Dhaka, especially during winter, with concentrations often exceeding both national standards and WHO guidelines [3].

To overcome the limitations of sparse ground-based networks, satellite-based fusion and machine learning methods have been developed. Mirzaei et al. [9] showed that combining MODIS and VIIRS AOD retrievals with an XGBoost fusion model improved $PM_{2.5}$ estimation in Tehran. Similarly, regression-based mapping of MODIS AOD in Iran illustrated the potential of hybrid models for data-scarce regions [10]. These studies highlight the promise of satellite–ground fusion approaches, but they also underline the continuing need for reliable ground-level calibration, which remains inadequate in Dhaka.

At the same time, optimization of sensor placement has gained significant attention in environmental monitoring. Wang et al. [11] presented a transformer-guided framework for climate sensor siting and showed that learned policies can outperform greedy variance reduction approaches. In a related direction, Kelp et al. [12] developed a data-driven method that explicitly incorporates equity considerations, demonstrating how $PM_{2.5}$ monitoring infrastructure can be placed to better serve disadvantaged urban communities.

Despite these developments, reinforcement learning has not yet been applied to static deployment of low-cost micro-networks for $PM_{2.5}$ mapping in Dhaka. Given the city's dense population, traffic-related hotspots, and strong seasonal variation, this gap represents a unique research opportunity. Applying RL-based sequential decision-making to sensor siting could enable adaptive placement strategies that balance accuracy, equity, and cost-effectiveness, which are still missing in much of the current literature.

5. Proposed Methodology

The proposed method is a quantitative approach, formulating sensor deployment as a sequential decision-making problem using Reinforcement Learning (RL).

5.1 Data Collection and Preprocessing

Datasets will be fused to build a Dhaka-specific simulation environment. Ground monitoring data will be collected from the Department of Environment (DoE) or Continuous Air Monitoring Stations (CAMS). Satellite datasets such as MODIS/MISR and Sentinel-5P will provide Aerosol Optical Depth (AOD), while ERA5 reanalysis and Bangladesh Meteorological Department data will supply meteorological features. Auxiliary datasets, including OpenStreetMap (road networks, land use) and population density maps, will enrich the spatial representation.

5.2 Problem Formulation

Sensor placement will be defined as a Markov Decision Process (MDP). The state space will include land use, traffic density, industrial presence, meteorological conditions, population, and currently deployed sensors. Actions correspond to placing sensors at feasible sites such as ward centroids, rooftops, or roadside poles. The reward will be defined as negative RMSE of $PM_{2.5}$ reconstruction, with additional penalties for inequitable coverage and infeasible siting.

5.3 Simulator Design

A surrogate environment will generate high-resolution $PM_{2.5}$ fields by fusing satellite, meteorological, and ground data. Seasonal variation and emission spikes will be modeled to ensure robustness. The simulator will return observations and rewards for RL training.

5.4 Reinforcement Learning Framework

Proximal Policy Optimization (PPO) will be used as the primary RL algorithm, leveraging CNN+MLP encoders for spatial feature extraction. Alternatives such as Soft Actor-Critic (SAC) and graph-based RL will also be explored for comparison. The implementation will be carried out in Python using PyTorch and Stable Baselines3, with a custom Gym-style environment for reproducibility.

5.5 Baseline Comparisons

RL performance will be benchmarked against random placement, greedy variance reduction, k-medoids clustering, and Gaussian Process variance minimization. These baselines will enable a clear evaluation of RL's effectiveness relative to established siting techniques.

5.6 Evaluation Metrics

Performance will be evaluated through reconstruction accuracy (RMSE and MAE), predictive variance reduction, equity of coverage measured by ward-level error distribution and the Gini coefficient, cost-effectiveness in terms of accuracy per sensor, and robustness across seasonal and emission scenarios.

Where possible, external validation will use withheld ground stations or mobile transects. Beyond technical evaluation, results will be interpreted for their implications in enabling equitable, cost-effective, and scalable air quality monitoring strategies in Dhaka and comparable megacities.

6. Expected Outcomes

The proposed study is expected to demonstrate that RL-trained policies outperform traditional siting methods by achieving lower RMSE and improved ward-level equity in air quality mapping for Dhaka. The outcomes will include deployment maps identifying optimal sensor locations under different budget scenarios (e.g., 10, 25, 50 sensors), enabling cost-effective and equitable monitoring strategies. An open-source Dhaka-specific air quality siting simulator and benchmark framework will be developed, along with trained RL policies and reproducible code to support future research.

7. Project Practicalities

The project will run over six months, utilizing public datasets such as satellite imagery, meteorological records, and OpenStreetMap to avoid reliance on costly primary data. Implementation will be carried out in Python using TensorFlow/PyTorch and reinforcement learning libraries, supported by a modest GPU setup. The workflow includes data preprocessing, simulator construction, baseline and RL policy training, followed by validation, analysis, and release of reproducible code.

8. Limitations

The project relies on satellite-derived data and limited ground truth, which may introduce bias and reduce the accuracy of simulated evaluations compared to real deployment conditions. Computational complexity for large spatial grids and data gaps in local monitoring networks may further constrain robustness. In addition, reinforcement learning policies risk overfitting to simulated environments, while operational challenges such as rooftop permissions and site accessibility can affect the feasibility of real-world sensor placement.

9. Post-Programme Plan

In the short term, the project will refine RL policies, enhance simulator fidelity, and release an open-source Dhaka AQ benchmark along with a policy brief. Medium-term efforts will focus on piloting small-scale sensor micro-networks in collaboration with NGOs and municipal bodies. In the long term, the framework will be extended to hybrid mobile–fixed deployments, multi-pollutant mapping, and adaptation to other megacities.

10. Novelty

The novelty of this project lies in applying reinforcement learning to static urban air-quality micro-network siting, a domain where existing methods are dominated by Gaussian Processes, information-gain, or clustering approaches. Unlike prior work, it integrates equity and real-world feasibility constraints into the reward design, making it directly applicable to Dhaka's dense and heterogeneous urban context.

11. Ethical & Social Considerations

Data privacy will be maintained by relying only on aggregated, publicly available datasets, while real-world sensor placements will avoid private property and require community consent. Equity is embedded into the design by ensuring that vulnerable wards are prioritized in coverage objectives. Finally, transparency will be upheld by openly releasing the models, assumptions, and methodologies for public scrutiny and ensuring accountability.

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