

Calibration of Low-Cost Particulate Matter Sensors for Urban Air Quality Monitoring

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Abstract— Low-cost particulate matter (PM) sensors make dense air quality networks affordable, but their readings drift with humidity and temperature and differ from reference instruments. This paper co-locates low-cost sensors with a reference monitor and compares linear, multiple-regression and random-forest calibration models. Calibration that includes relative humidity and temperature reduces error substantially. The paper provides a practical procedure that schools and community groups can follow. All values are sample data for this template.

Index Terms— air quality, low-cost sensors, PM2.5, calibration, Internet of Things

This is a template: all data, results and references are placeholders for the author to replace.

I. INTRODUCTION

Fine particulate matter (PM_{2.5}) is a major air pollutant in many cities. Reference-grade monitors are accurate but expensive, so monitoring stations are sparse and may not reflect conditions in individual neighbourhoods.

Low-cost optical sensors can fill these gaps, but their raw readings are affected by humidity, temperature and particle composition. Calibration against a reference monitor is essential before their data can be trusted.

The main contributions of this paper are as follows:

- A two-month co-location study of low-cost sensors with a reference monitor.
- A comparison of three calibration models using environmental variables.
- A simple field procedure for calibrating community sensor networks.

The rest of the paper is organised as follows. Section II reviews related work, Section III describes the proposed calibration model, Section IV presents the experimental setup, Section V reports and discusses the results, and Section VI concludes the paper.

II. RELATED WORK

Field studies report that raw low-cost sensor readings can overestimate PM_{2.5} during humid conditions [1].

Linear correction factors improve agreement but do not handle non-linear humidity effects [2].

Machine-learning calibration models have achieved lower errors in several cities [3].

Long-term drift requires periodic recalibration [4].

III. PROPOSED CALIBRATION MODEL

Sensors were installed next to a reference monitor at a height of three metres. Each node recorded PM_{2.5}, temperature and relative humidity every minute; readings were averaged to hourly values.

Three calibration models were trained on the first five weeks of data and tested on the remaining three weeks.

A. Overview

Each sensor node uses a microcontroller with Wi-Fi to send readings to a server, where hourly averages are computed and the calibration model is applied.

Figure placeholder — block diagram of the proposed calibration model

Fig. 1. Overview of the proposed calibration model

B. Algorithm

1. Co-locate sensors with the reference monitor.
2. Collect and clean minute-level data.
3. Compute hourly averages.
4. Train calibration models on the training period.
5. Apply models to the test period and compare errors.

$$PM_{cal} = \beta_0 + \beta_1 \cdot PM_{raw} + \beta_2 \cdot RH + \beta_3 \cdot T$$

IV. EXPERIMENTAL SETUP

Four sensor nodes were co-located for eight weeks during the winter season. The reference monitor provided hourly PM_{2.5} values. Models were trained on five weeks and tested on three.

Parameter	Value
Sensor nodes	4
Duration	8 weeks
Averaging	1 hour
Train / test	5 / 3 weeks
Variables	PM _{2.5} , RH, T

Parameter	Value
Models	Linear, MLR, random forest

TABLE II. Experimental parameters

A. Evaluation Metrics

- Coefficient of determination (R^2)
- Root mean square error (RMSE, $\mu\text{g}/\text{m}^3$)
- Mean absolute error (MAE, $\mu\text{g}/\text{m}^3$)

V. RESULTS AND DISCUSSION

Including humidity and temperature improved agreement with the reference monitor. The random-forest model performed best on the test period.

Model	R^2	RMSE ($\mu\text{g}/\text{m}^3$)	MAE ($\mu\text{g}/\text{m}^3$)
Raw readings	0.61	38.2	29.5
Linear correction	0.72	24.6	18.1
Multiple regression (PM, RH, T)	0.84	17.3	12.4
Random forest	0.89	13.8	9.9

TABLE III. Comparison with baseline methods (sample data)

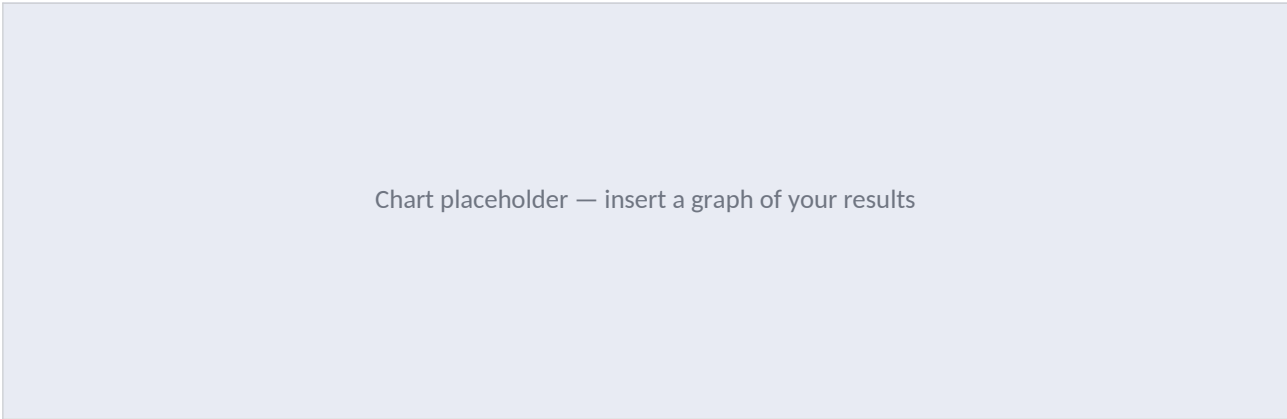


Fig. 2. Calibrated versus reference PM2.5 for the test period (sample data)

Errors were highest when relative humidity exceeded 85%, confirming the need for humidity terms.

Differences between individual sensors were small after calibration, which supports the use of a single model per sensor type.

VI. CONCLUSION AND FUTURE WORK

Calibration with environmental variables makes low-cost PM sensors far more reliable for neighbourhood monitoring.

Future work will study seasonal drift, transfer of models between locations and automatic recalibration using nearby reference stations.

Acknowledgment

The authors thank the department and the participants who helped with data collection. Replace this paragraph with your own acknowledgment, including any funding support.

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