Applying machine learning for large scale field calibration of low-cost PM$_{2.5}$ and PM$_{10}$ air pollution sensors

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Introduction

- Ambient air pollution is a major environmental health risk in cities all over the world with harmful effects on human health and the ecosystem. It causes 4.2 million deaths per year.
- Ambient air quality data collection is done using reference grade monitors, e.g., the Beta Attenuation Monitor (BAM) which measures Particulate Matter (PM).
- They are highly accurate, but remain scarce in many cities in low & middle-income countries.
- Low-cost air quality monitors (LCAQMs) are increasingly being adopted as a complementary approach to fill the air quality data gaps while increasing spatial resolution of air quality data.
- We demonstrate the feasibility of using machine learning (ML) methods for large-scale calibration of AirQo low-cost PM sensors.

The low-cost sensor calibration challenge

LCAQMs are more error prone than reference grade monitors.
- Their accuracy degrades over time
- They can be affected by external factors such as weather changes
- They suffer from cross-sensitivities between different ambient pollutants
- Sensor calibration is crucial for LCAQMs to ensure data quality and reliability
- This involves using appropriate statistical methods to correct measurements from low-cost sensors and validating against reference-grade monitors

In this research study, we used AirQo LCAQMs and investigated:
- ML approaches for sensor calibration on a large scale air pollution network in urban environments with relatively high levels of particulate matter concentrations and variations
- The issues involved in deploying such ML-based calibration models to a production system

Materials and Methods

Study Locations

We considered a real world air quality monitoring network with over 120 nodes deployed in cities with in Uganda. The experimental setup for the calibration included two monitoring sites.

Data collection and pre-processing

- PM data was collected using a total of 8 AirQo devices & 2 BAMs collocated at reference site 1 between 15th July 2020 & 17th July 2021 & reference site 2 from 20th Sept to 26th Oct 2021
- Met data (temperature & humidity) from the BAMs and from TAHMO stations was used.
- The average data completeness for all devices used in this study was approximately 87.61%.

Algorithm selection and validation

- We evaluated the performance of various ML algorithms for low-cost PM$_{2.5}$ and PM$_{10}$ calibration.
- These included KNN, SVM, Multivariate Linear Regression, Multi-layer Perceptron, Random Forest (RF), XGBoost, ridge, lasso and elastic net regression.
- Performance of different algorithms was evaluated using the same training & validation datasets.
- Performance evaluation was done using the RMSE, MAE, $R^2$ and Pearson’s correlation coefficient.

Input variable selection

- We selected the best variable combinations using variables including hourly PM$_{2.5}$ & PM$_{10}$ from the low-cost sensor, atmospheric temperature (AT), RH, features derived from timestamp (month and hour/3h), features from PM including $\text{co}\text{var}$ PM$_{2.5}$, $\text{co}\text{var}$ PM$_{10}$, PM$_{2.5}$ − PM$_{10}$.

Algorithm validation methods

- Cross unit validation: We conducted performance evaluation for the proposed models using data from other AirQo devices within the same site.
- Cross site validation: We conducted performance evaluation for the proposed models using other AirQo devices collocated with the BAM at another reference site.

Algorithm selection

Best performance was achieved using variable combinations in equations 1 & 2 for PM calibration.

\[
\text{Target PM}_{2.5} = \beta_0 + \beta_1 \text{PM}_{2.5} + \beta_2 \text{RH} + \beta_3 \text{PM}_{2.5} \text{co}\text{var} \text{PM}_{2.5} + \beta_4 \text{Month} + \beta_5 \text{hour/3h}.
\]

(1)

RF had the best performance for PM$_{5}$ calibration

Lasso regression had the best performance for low-cost PM$_{10}$ calibration

Study Results

- Table 1. Random forest using optimal parameters and various input variable combinations.

<table>
<thead>
<tr>
<th>Input variables</th>
<th>RMSE (µg/m$^3$)</th>
<th>MAE (µg/m$^3$)</th>
<th>$R^2$</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factory calibrated(PM$_{2.5}$)</td>
<td>10.4</td>
<td>6.92</td>
<td>0.92</td>
<td></td>
</tr>
<tr>
<td>Factory calibrated(PM$_{10}$)</td>
<td>10.4</td>
<td>6.92</td>
<td>0.92</td>
<td></td>
</tr>
<tr>
<td>PM$_{2.5}$, AT, RH</td>
<td>9.3</td>
<td>5.6</td>
<td>0.94</td>
<td></td>
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<tr>
<td>PM$<em>{2.5}$, AT, RH, PM$</em>{2.5}$ co$\text{var}$PM$<em>{2.5}$, PM$</em>{2.5}$ − PM$_{10}$</td>
<td>9.1</td>
<td>5.3</td>
<td>0.88</td>
<td>0.94</td>
</tr>
<tr>
<td>PM$<em>{10}$, AT, RH, PM$</em>{10}$ co$\text{var}$PM$<em>{10}$, PM$</em>{2.5}$ - PM$_{10}$</td>
<td>8.5</td>
<td>5.1</td>
<td>0.90</td>
<td>0.95</td>
</tr>
<tr>
<td>PM$<em>{10}$, AT, RH, PM$</em>{10}$ co$\text{var}$PM$<em>{10}$, PM$</em>{2.5}$ - PM$_{10}$ month</td>
<td>7.4</td>
<td>4.8</td>
<td>0.92</td>
<td>0.96</td>
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<tr>
<td>PM$<em>{10}$, AT, RH, PM$</em>{10}$ co$\text{var}$PM$<em>{10}$, PM$</em>{2.5}$ - PM$_{10}$ month, hr</td>
<td>7.2</td>
<td>4.6</td>
<td>0.92</td>
<td>0.96</td>
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<tr>
<td>Collected BAM (Benchmark)</td>
<td>6.2</td>
<td>4.1</td>
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Table 2. Lasso regression using optimal parameters and various input variable combinations.

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Deployment of calibration models in production

- The models are deployed as part of an urban air quality sensing system that is accessible to users via an open air quality API, an analytics dashboard https://platform.airqo.net, and a mobile app.
- The calibration models are encapsulated as a microservice that are exposed as REST APIs.
- Raw measurements from all devices on the network are streamed to a cloud-based iQST platform.
- Raw hourly PM concentrations are fed into the calibration models with corresponding hourly temperature & humidity readings to generate corresponding calibrated PM concentrations.
- The deployment serves as a demonstration of the use of a Machine Learning system in addressing society challenges, in this case ambient urban air pollution.

Conclusion and Discussion

- Various ML methods were compared for AirQo device calibration, with RF and lasso regression performing well for PM$_{2.5}$ and PM$_{10}$ calibration respectively.
- RF model tends to under-predict spikes but excluding spikes lead to improved accuracy.
- We achieved reasonable accuracy with cross-unit and cross-site validation hence AirQo monitors do not have to be calibrated individually.
- Retention of the models is important in order to cater for seasonal and condition-specific dependency of calibration factors.

References