Performance Comparison of Low-Cost Sensors Across Six Cities of Continental United States

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PERFORMANCE COMPARISON OF LOW-COST SENSORS ACROSS SIX CITIES OF CONTINENTAL UNITED STATES

by

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B.S. Bangladesh University of Engineering and Technology, 2018

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Department of Civil, Environmental, and Construction Engineering in the College of Engineering and Computer Science at the University of Central Florida Orlando, Florida

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Major Professor: Haofei Yu
ABSTRACT

In the field of air quality measurement, low-cost sensors have been extensively used for capturing high-resolution spatial and temporal pollutant concentrations. However, data accuracy and the impact of environmental conditions particularly temperature and relative humidity, remain a significant issue. Careful sensor calibrations against reference instruments are necessary for ensuring data accuracy and validity. This study investigated the effectiveness of multiple calibration methodologies (linear calibration, 3rd order polynomial calibration, and Random Forest) for low-cost air quality sensor calibration across six cities (Atlanta, Portland, Riverside, Sacramento, New York City, and Phoenix) in the United States. The data for this study is collected from April 2019 to April 2020 in the corresponding cities. The study showed that the local calibration provides better accuracy than adopting calibration equation developed for other regions across all the models tested. The potential reasons could be that different cities may have different pollution source combinations, which may result in varying types and concentration levels of interfering gas. Different weather conditions will also contribute to such results, as parameters especially temperature and relative humidity are known to impact the performance of low-cost sensors. Additionally, if included CO signal in the calibration models of NO2 and O3, model performances are found to increases across all the cities. Low-cost CO sensor is known to generally perform better and has better long-term stability than their NO2 and O3 sensor counterparts. Results of this thesis contribute to better understanding on low-cost air pollutant sensor deployment and calibration techniques.
ACKNOWLEDGMENTS

I would like to express deep gratitude to my supervisor, Dr. Haofei Yu, for his valuable guidance and support in the process of developing this thesis. I would also like to gratefully acknowledge Dr. Yi Li, for his support in the data collection process.
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CHAPTER 1: INTRODUCTION

1.1 Background

Air pollution is an important environmental and public health issue in the 21st century. Air pollution can be defined as one or more substances present in the air in quantities that is detrimental for human health and/or the ecosystem. (Manisalidis et al., 2020) Exposure to air pollution can results in numerous adverse health issues including but not limit to lung cancer, blood vessel function impairment, lowering levels of good cholesterol which consequently increased risk of cardiovascular disease, maternal illness (e.g., low birth rates and fetal illness) and respiratory disease (e.g., asthma and chronic bronchitis). (Brunekreef & Holgate, 2002) Children, older population, pregnant women and people who are already suffering from respiratory disease are most vulnerable to the negative impacts of air pollution. (Peled, 2011)

Air pollution management is necessary to reduce air pollution and mitigate the heath impact air pollution on human health. (Chandrappa & Kulshrestha, 2015) Transportation management, renewable energy promotion, control of emission from industries sources such as power plants, urban planning and promoting public awareness on the detrimental impact of pollution are some of the steps of air pollution management. (Sofia et al., 2020)

Concentration monitoring with an urban region is one of the regulatory tools for air pollution management. (Gulia et al., 2015) The National Ambient Air Quality Standard (NAAQS) is the US-wide standard for concentration limits of important ambient air pollutants called Criteria Air Pollutants (CAPs). (Dimantchev, 2018) A region that is violating the NAAQS standard will face
mandatory and expensive control policy requirement from United States Environmental Protection Agency (USEPA). (Schreiber et al., 2017) For regulatory purposes, federally approved reference instruments are used nationwide across all monitoring stations for NAAQS compliance determination. (Hasan et al., 2023) Suitable site selection, deployment of instruments, instrument calibration, data collection and validation are some of the steps of regulatory monitoring and all have strict procedure requirements. (Morawska et al., 2018) Sampling sites are often required to not be adjacent to major pollution sources to capture representative population-level exposures thus common pollution hotspots are not sufficiently captured. (Ott, 1977)

In addition, regulatory monitoring requires the use of equipment with Federal Reference Methods (FRM) or Federal Equivalent Methods (FEM) certifications. The instruments are bulky, expensive and requires skilled personnel for maintenance and calibration. High spatial resolution pollutant concentration measurement is not possible using FRM measurement. (Kelly et al., 2017) However, concentrations of several important CAPs are known to vary significantly in short distances. (Jerrett et al., 2017 and Do et al., 2021)

Low cost IoT enabled sensors can work to supplement Federal Reference (FRM) or Federal Equivalent (FEM) methods. Low Cost Air Quality (LCAQ) sensors are one or more embedded sensor that measures particle and gaseous pollutant concentration and costs much less than FRM/FEM instruments. LCAQ sensors are easier to deploy and have lower up-front capital and maintenance costs per unit, thus also making them ideal for citizen engagement, providing new avenues for public education on environmental science and technology, advancing citizen science, and contributing to sustainable social development. (Kaginalkar et al., 2021 and Kumar et al., 2015)
On the other hand, low-cost sensors have several limitations. Accuracy issue against reference instruments (Collier-Oxandale et al., 2020), precision or inter unit variability (Liu et al., 2019), environmental impact (Kang et al., 2022 and Samad et al., 2020) and long-term stability (Liu et al., 2020) are some of the issues associated with LCAQ sensors. Gaseous LCAQ sensors have cross sensitivity (sensor designed for target gas is sensitive to other gases) issue. (Lewis et al., 2018 and Mead et al., 2013) The performance of many LCAQ sensors is favorable under controlled laboratory conditions but their accuracy in the ambient environment could vary substantially among deployment locations. (Castell et al., 2017 and Karagulian et al., 2019)

LCAQ sensor calibration by co-location with research-grade equipment preferably federal reference or federal equivalent instruments is necessary to improve accuracy. Many types of mathematical models are being used for calibration purpose. For example, linear regression is mostly used as a calibration model by assumption that sensor signal linearly changes with the change of pollutant concentration. (Mijling et al., 2018, Spinelle et al., 2017, Bigi et al., 2018 and van Zoest et al., 2019) But linear calibration is sometimes found to be not effective for field calibration (as opposed to calibration under controlled laboratory environment) especially for gaseous monitors. As a result, non-linear models and machine learning models been increasingly used recently for sensor calibration to improve accuracy. (Zimmerman et al., 2018 and Malings et al., 2019) Calibration equation generated for one location might not be effective for another location because of the varying pollutant sources, meteorology and particle characteristics. Previous researches did not perform LCAQ sensor calibration based on sensor relocation to different cities with varying meteorology, terrain and pollutant sources. Additionally, field calibration accuracy of NO₂ and O₃ electrochemical sensors is much lower than CO
electrochemical sensor especially in high temperature. CO sensor signal inclusion in the model could improve other electrochemical sensor performances.

In our study, we investigate the performance of LCAQ sensors among different cities across the continental United States. This includes comparing the performance of LCAQ sensors under local conditions against when calibrated in a different region. The study will also investigate the possible cross-sensitivity of CO gas signal in electrochemical low-cost sensor performances.

The rest of the thesis is organized as follows: Chapter 2 describes the study on low-cost electrochemical sensor (NO₂ and O₃) calibration by incorporating CO sensor signal across six US cities. Chapter 3 describes the study on the performance of LCAQ sensor calibration models among different cities. Finally, an overall summary and conclusions of the two studies is presented.
CHAPTER 2: PERFORMANCE IMPROVEMENT OF ELECTROCHEMICAL SENSORS BY INCLUDING CO SENSOR SIGNAL

2.1 Introduction

Recent advancements in pollution measurement and Internet-of-Things (IoT) technologies have enabled the rapid evolution of low-cost air pollution sensors, which have gained tremendous attention in recent years, (Hall et al., 2014 and Castell et al., 2017) allowing a paradigm shift in air quality monitoring. (Snyder et al., 2013) For less than $2500 per pollutant, these low-cost air quality (LCAQ) sensors can be deployed in significantly greater numbers to expand the capabilities of the existing air pollution monitoring network, thereby extending the spatial and temporal resolution of estimated pollutant concentrations. (Becnel et al., 2019, Qin et al., 2020, Liu et al., 2005 and Caubel et al., 2019) In addition, LCAQ sensors are easier to deploy and have lower up-front capital and maintenance costs per unit, thus making them ideal for citizen engagement, providing new avenues for public education on environmental science and technology, advancing citizen science, and contributing to sustainable social development. (Conrad et al., 2011 and Riesch et al., 2014) Despite the advantages, the measurement data collected from LCAQ sensors also contain substantial uncertainties. (Karagulian et al., 2019, Morawska et al., 2018 and Bulot et al., 2019) The impact of environmental conditions, such as temperature, humidity and the presence of interfering
chemical species, has proven to contribute most to these uncertainties. (Collier-Oxandale et al., 2020, Feenstra et al., 2019 and Mijling et al., 2018) In addition, most past studies on sensor uncertainties focused on a single pollutant at a single geographical location. (Mijling et al., 2018, Lewis et al., 2016 and Smith et al., 2017) For example, field evaluations performed by the well-known Air Quality Sensor Performance Evaluation Center (AQ-SPEC) program (http://www.aqmd.gov/aq-spec) were conducted at a single site in Southern California. On the other hand, FRM/FEM instruments are required to be evaluated in at least four sites with distinct climatological conditions. Studies on how LCAQ sensors with the capability of multi-pollutant monitoring perform across locations with different climate conditions remain limited. (Malings et al., 2020, Ripoll et al., 2019, Zheng et al., 2018, Johnson et al., 2018 and Zusman et al., 2020) A better understanding of how LCAQ sensors perform under different cities with heterogenous environmental conditions and how to develop proper calibration models for LCAQ sensors is critical for developing practical calibration algorithms and improving the data quality of connected sensor networks.

In this section of the study, we evaluated and compared the performance of a commercially available LCAQ electrochemical sensor (Model SCI-608 monitor, Sailbri Cooper Inc., Portland, Oregon) at six locations with different climate conditions across the continental United States.  

2.2 Exploratory Data Analysis

Commercially available LCAQ electrochemical sensor (Model SCI-608 monitor, Sailbri Cooper Inc., Portland, Oregon) was installed at six locations with different climate conditions across the continental United States. (Figure 1) Detailed information on the co-ordinate and elevation of the locations are provided in Table 1. The temperature of the locations was ranging from 24.8 to 111.5 °F and relative humidity (RH) ranging from 12 to 101%. Atlanta and New York City have
a humid subtropical climate. Sacramento and Portland have a hot-summer and a warm-summer Mediterranean climate, respectively. On the other hand, Riverside’s climate is semi-arid and Phoenix has a hot desert climate. Naturally, during deployment, meteorological conditions among the six cities varied considerably (Table 2). Hourly mean temperatures were relatively high in Atlanta (28.3 °C) and Riverside (26.9 °C) but low in New York (7.5 °C). Hourly mean relative humidity (RH) ranged from a moderate value of 48% (in Sacramento) to a relatively high value of 72% in Atlanta. The drastically different climates among the six cities make them ideal for comparing the performance of low-cost sensors under different environmental conditions.

![Figure 1: Locations of the Measurement Stations](image)

Pollution concentration levels are relatively similar for CO and NO₂ but differ for O₃ among the six cities (Table 2). Moderate NO₂ levels were observed, with mean levels ranging from 7.4 ppbv (Atlanta) to 15.5 ppbv (Phoenix). Elevated O₃ levels were observed in Riverside (up to 126 ppbv,
substantially higher than in the other five cities). CO concentration levels are generally low among all five cities where data are available.

The SCI-608 is capable of measuring six pollutants and meteorological parameters, including particulate matter with an aerodynamic diameter less than or equal to 10 μm (PM$_{10}$) and less than or equal to 2.5 μm (PM$_{2.5}$), ozone (O$_3$), carbon monoxide (CO), nitrogen dioxide (NO$_2$), sulfur dioxide (SO$_2$), temperature, and RH. It has been used in several previous ambient measurement studies. (Li et al., 2022 and Chen et al., 2020) In this part of the study, we focus our discussion on the measurements of gaseous pollutants, specifically CO, NO$_2$, and O$_3$. SO$_2$ is not discussed due to the low ambient concentration in most cities (below the instrument detection limit). PM$_{2.5}$ and PM$_{10}$ are not discussed in this part of the study.

### 2.3 Method

The SCI-608 monitor houses multiple sensors designed for particulate matter (PM) and gaseous pollutants. One laser optical particle counter (PM2005, Cubic Sensor and Instrument Co., China)

<table>
<thead>
<tr>
<th>Location</th>
<th>Site Name</th>
<th>Latitude (N)</th>
<th>Longitude (W)</th>
<th>Elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta, GA</td>
<td>South DeKalb</td>
<td>33.69</td>
<td>84.29</td>
<td>308</td>
</tr>
<tr>
<td>Riverside, CA</td>
<td>Mira Loma</td>
<td>33.99</td>
<td>117.49</td>
<td>220</td>
</tr>
<tr>
<td>Sacramento, CA</td>
<td>1309 T St.</td>
<td>38.57</td>
<td>121.49</td>
<td>30</td>
</tr>
<tr>
<td>New York City, NY</td>
<td>Queens College II</td>
<td>40.74</td>
<td>73.82</td>
<td>25</td>
</tr>
<tr>
<td>Portland, OR</td>
<td>SE Lafayette</td>
<td>45.5</td>
<td>122.6</td>
<td>69</td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>JLG Supersite</td>
<td>33.5038</td>
<td>112.1</td>
<td>354</td>
</tr>
</tbody>
</table>
was used for PM measurement, four electrochemical sensors (B4 series, Alphasense, U.K.) were used for gaseous pollutants, and one meteorological sensor (SHT21, Sensirion) was used for relative humidity and temperature. The optical particle counter (OPC) counts the number of particles within different size ranges based on the laser scattering principle. The OPC converts particle numbers to particle mass concentrations using proprietary algorithms. The electrochemical sensors estimate pollutant concentrations by measuring

Table 2: The details of sensor deployment including the range of temperature, humidity, 1-hour average FRM/FEM concentration (range is in the parenthesis mean is outside of parenthesis) and of NO$_2$, O$_3$ and PM$_{2.5}$

<table>
<thead>
<tr>
<th>Location</th>
<th>Temperature ($^\circ$C)</th>
<th>RH (%)</th>
<th>NO$_2$(ppbv)</th>
<th>O$_3$(ppbv)</th>
<th>PM$_{2.5}$(µg/m$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlanta, GA</td>
<td>28.3 (17-40.5)</td>
<td>72 (31.7-97.4)</td>
<td>7.4 (1-38)</td>
<td>28.5 (1-77)</td>
<td>10.2 (2.8-26.8)</td>
</tr>
<tr>
<td>New York City, NY</td>
<td>7.5 (-9-23.9)</td>
<td>62.5 (22.2-101)</td>
<td>13.9 (1.1-53.7)</td>
<td>28.8 (1-58)</td>
<td>7.04 (0.6-31.1)</td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>15.7 (0-34.3)</td>
<td>52.3 (16.9-98.3)</td>
<td>15.5 (2-50)</td>
<td>20.6 (1-56)</td>
<td>10.64 (-4-250)</td>
</tr>
<tr>
<td>Portland, OR</td>
<td>14.7 (-4-40.2)</td>
<td>68.9 (17-103)</td>
<td>7.5 (1-42)</td>
<td>23.2 (1-77)</td>
<td>5.95 (0.9-58.8)</td>
</tr>
<tr>
<td>Riverside, CA</td>
<td>26.9 (16.1-44.2)</td>
<td>54.8 (15.3-90.1)</td>
<td>10.2 (2-31)</td>
<td>42.1 (2-126)</td>
<td>13.48 (2.9-37.3)</td>
</tr>
<tr>
<td>Sacramento, CA</td>
<td>17.6 (3-34.2)</td>
<td>48.1 (12-94.8)</td>
<td>17.1 (1-62)</td>
<td>23 (-2-66)</td>
<td>11.25 (-2-59)</td>
</tr>
</tbody>
</table>
current changes within the sensor as induced by chemical reactions with the target gas. The monitor can be powered by an AC power source or an optional solar panel. Measurement data collected by the monitor are transmitted to a centralized server via the cellular network, and a web-based interface is used to manage and visualize the collected measurement data.

In this study, we deployed six SCI-608 monitors to six regulatory monitoring stations located in six cities in the United States, including Portland, OR; Atlanta, GA; Riverside, CA; Sacramento, CA; New York, NY; and Phoenix, AZ., with corresponding FEM/FRM equipment models listed in Table 3.

SailHero performed internal screening procedures to identify and discard sensors with abnormal responses. (Cui et al., 2021) As an additional precaution measurement prior to field deployment, all monitors were first tested in Portland, OR (Site ID 41-051-00804) by collocating with FEM/FRM instruments for at least one week as a part of sensor QA/QC and then transported to and deployed in each city. All onsite reference data (FEM/FRM), including temperature and relative humidity in this research, were obtained through the EPA Air Quality System (AQS) application programming interface (API) (https://aqs.epa.gov/aqsweb/documents/data_api.html).

Measurement data from sensors were collected continuously, and the hourly average was computed. No down-sampling or pre-processing (other than averaging) was performed. Due primarily to logistic reasons, the six monitors were not deployed at the same time. The first monitor was installed in Portland on January 4, 2019, and the last monitor was installed in New York on January 28, 2020. The lengths of deployment varied, ranging from 20 days (Riverside) to 301 days (Portland), with an average deployment of 103 days due to site access and availability. All units were AC-powered, and no solar panels were used. Data completeness is 99% in Phoenix, AZ, and 100% in all other five cities.
We applied three methods, separately at each location, to develop sensor calibration models: simple linear regression, third order polynomial regression, and random forest (RF), all of which have been used in recent studies of low-cost gaseous sensor calibrations. (Bigi et al., 2018 and van Zoest et al., 2019)

Table 3: FRM/FEM instrument used in the study locations along with the data availability

<table>
<thead>
<tr>
<th>Location</th>
<th>NO₂</th>
<th>O₃</th>
<th>PM₂.₅</th>
<th>Data Availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Riverside, CA</td>
<td>Thermo Scientific 42i</td>
<td>Teledyne API 400E</td>
<td>Met One BAM 1020</td>
<td>8/2/2019-8/22/2019</td>
</tr>
<tr>
<td>New York City, NY</td>
<td>Thermo Scientific 42i</td>
<td>Teledyne API T400</td>
<td>Teledyne T640 and Gravimetric TEOM</td>
<td>1/28/2020-4/22/2020</td>
</tr>
<tr>
<td>Portland, OR</td>
<td>Teledyne API T500U</td>
<td>Teledyne API T400</td>
<td>Gravimetric, R&amp;P</td>
<td>1/4/2019-10/31/2019</td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>Teledyne API T500U</td>
<td>Teledyne API T400</td>
<td>Met One BAM 1020 and Thermo Partisol</td>
<td>12/11/2019-4/14/2020</td>
</tr>
</tbody>
</table>
We applied equation 1 in the linear method.

\[ C_p = aS_p + bT + cRH + d \] ………………………………………………………………………………………………………………… (1)

where \( C_p \) is the concentration (ppbv) of pollutant p as measured by the FRM/FEM instrument; \( S_p \) is the uncorrected electrode voltage (mV) from sensors, which was set to raw \( \text{NO}_2 \) sensor voltage for \( \text{NO}_2 \) calibration and \( \text{O}_3 \) sensor response with the \( \text{NO}_2 \) signal subtracted for \( \text{O}_3 \) calibration (done due to the physical design of electrochemical sensors used in SCI-608); \( T \) is the temperature (°C); RH is the relative humidity; and \( a, b, c, \) and \( d \) are the linear regression coefficients. To keep the data conformity, \( T \) and RH data used in this study were measured by FRM/FEM equipment but not from low-cost sensors.

We applied equation 2 for polynomial method.

\[ C_p = aS_p^3 + bT^3 + cRH^3 + d \] ………………………………………………………………………………………………………………… (2)

We utilized random forest method also for this study which is a widely used non-parametric machine learning algorithm for supervised classification and regression analysis. It is an advanced version of bagging or bootstrap aggregation which fits many large decision trees to bootstrapped resampled data and classify by majority vote or predict by taking mean. Random forest models improve the traditional bagging algorithms by de-correlating the trees and reducing the variance. The number of trees in the random forest regression across all the calibration of our study was 100 based on sensitivity analysis. All other parameters, such as maximum tree depth, were also selected based on sensitivity analysis.

There are two evaluation matrices that were used to evaluate the performances of the calibration models, coefficient of determination (\( R^2 \)) and root mean square error (RMSE). \( R^2 \) is the variance of the dependent variable that can be predicted by the independent variable. It is a method of
assessing the fitness of the model. It is the square of the strength of the linear relationship between observed concentration (FRM/FEM concentration) and predicted concentration (concentration derived from the calibration models). \( R^2 \) varies from 0 to 1 with a value closer to 1 indicating that the predicted pollutant concentration has good agreement with the actual pollutant concentration gathered from FRM/FEM instruments. Lower \( R^2 \) values (closer to 0) indicate that the predicted pollutant concentration data has a poor correlation with the actual FRM/FEM data. RMSE provides the error in the model by calculating the distance between the predicted concentration and the actual concentration. Good model performance can be validated by a lower value of RMSE.

2.4 Result and Discussion

2.4.1 Sensor Performance

All sensors in the SCI-608 monitor were directly exposed to ambient air, with no pre-conditioning. Sensor calibration was performed using three different methods: linear, third-order polynomial, and random forest (RF). Model performance was evaluated by comparing the coefficient of determination \( (R^2) \) and root-mean-square error (RMSE) for each model. Figure 2 provides a time-series plot of hourly NO\(_2\) concentration at Portland, as collected by FRM/FEM equipment and from low-cost sensors calibrated using three different methods. Time-series plots of FRM/FEM data and calibrated concentrations for other pollutants and at other cities are provided in Figures 16 through 27. The performances of the three methods are different, particularly regarding their capability of capturing low and high concentrations. The linear calibration method even resulted in negative concentrations.
Figure 2: Time-series plot of hourly NO$_2$ concentrations at Portland as collected by FRM/FEM equipment and from low-cost sensors with linear, polynomial, and random forest calibration

Performances of the six SCI-608 monitors varied considerably among the six cities (Table 4 for $R^2$ and Table 5 for RMSE) and were not consistent for NO$_2$ and O$_3$. For example, the Atlanta and Riverside LCAQ sensors perform relatively poorly against the reference data for NO$_2$, with $R^2$'s of only 0.34 and 0.26, respectively, when using linear calibration. On the other hand, these two sensors perform relatively well for O$_3$ (linear $R^2 = 0.81$ at Atlanta and 0.97 at Riverside). On the contrary, the Sacramento and New York monitors perform well for NO$_2$ (linear $R^2 = 0.83$ and 0.84, respectively) but relatively poor for O$_3$ (linear $R^2 = 0.59$ and 0.23, respectively). In Portland and Phoenix, the performances of the two sensors are relatively consistent between NO$_2$ and O$_3$. In Atlanta and Riverside, the relatively poor NO$_2$ sensor performances may be attributable to high temperature and humidity conditions, the impacts of which on the performances of electrochemical NO$_2$ sensors have been reported in other studies. (Mijling et al., 2018, Lewis et al., 2016 and Wei et al., 2020) Relatively high $R^2$ values may be partially due to the considerable O$_3$ concentration reported at the two cities (maximum 1 h ozone concentration of 77 ppbv at Atlanta and 126 ppbv at Riverside) during summertime.

Among the three different sensor calibration methods, the RF method performs the best. However, using different methods did not change the inconsistent performances between NO$_2$ and O$_3$ sensors. Scientists from AQ-SPEC have conducted batch field tests of NO$_2$ and
O3 sensor from various manufacturers, 11 of which are based on electrochemical technology. According to the results summarized in Table 6, the performance of the O3 sensor is consistently better than the NO2 one.

Table 4: Sensor performance ($R^2$) at corresponding cities, without CO data. Excellent performance ($R^2 > 0.8$) is bolded

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Portland</th>
<th>Atlanta</th>
<th>Riverside</th>
<th>Sacramento</th>
<th>New York</th>
<th>Phoenix</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear</td>
<td>0.73</td>
<td>0.34</td>
<td>0.26</td>
<td><strong>0.83</strong></td>
<td><strong>0.84</strong></td>
<td>0.51</td>
</tr>
<tr>
<td>Polynomial</td>
<td><strong>0.83</strong></td>
<td>0.37</td>
<td>0.20</td>
<td><strong>0.88</strong></td>
<td><strong>0.88</strong></td>
<td>0.62</td>
</tr>
<tr>
<td>RF</td>
<td>0.84</td>
<td>0.65</td>
<td>0.48</td>
<td><strong>0.93</strong></td>
<td>0.90</td>
<td><strong>0.74</strong></td>
</tr>
<tr>
<td>O3</td>
<td>0.63</td>
<td><strong>0.81</strong></td>
<td><strong>0.97</strong></td>
<td>0.59</td>
<td>0.23</td>
<td>0.58</td>
</tr>
<tr>
<td>Polynomial</td>
<td>0.65</td>
<td>0.79</td>
<td><strong>0.95</strong></td>
<td>0.55</td>
<td>0.18</td>
<td>0.53</td>
</tr>
<tr>
<td>RF</td>
<td><strong>0.81</strong></td>
<td><strong>0.86</strong></td>
<td><strong>0.97</strong></td>
<td>0.82</td>
<td>0.39</td>
<td>0.70</td>
</tr>
<tr>
<td>CO</td>
<td><strong>0.91</strong></td>
<td>0.74</td>
<td>0.4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Polynomial</td>
<td><strong>0.9</strong></td>
<td>0.74</td>
<td>0.46</td>
<td>N/A</td>
<td><strong>0.94</strong></td>
<td><strong>0.97</strong></td>
</tr>
<tr>
<td>RF</td>
<td><strong>0.96</strong></td>
<td><strong>0.93</strong></td>
<td><strong>0.87</strong></td>
<td></td>
<td><strong>0.96</strong></td>
<td><strong>0.98</strong></td>
</tr>
</tbody>
</table>

Table 5: Sensor performance (RMSE) at corresponding cities, without CO data

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Portland</th>
<th>Atlanta</th>
<th>Riverside</th>
<th>Sacramento</th>
<th>New York</th>
<th>Phoenix</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear</td>
<td>3.48</td>
<td>4.29</td>
<td>4.39</td>
<td>5.99</td>
<td>4.37</td>
<td>7.51</td>
</tr>
<tr>
<td>Polynomial</td>
<td>2.78</td>
<td>4.19</td>
<td>4.56</td>
<td>5.09</td>
<td>3.74</td>
<td>6.66</td>
</tr>
<tr>
<td>RF</td>
<td>2.72</td>
<td>3.16</td>
<td>3.75</td>
<td>3.91</td>
<td>3.43</td>
<td>5.46</td>
</tr>
<tr>
<td>O3</td>
<td>7.84</td>
<td>7.8</td>
<td>5.65</td>
<td><strong>10.18</strong></td>
<td>10.32</td>
<td><strong>9.77</strong></td>
</tr>
<tr>
<td>Polynomial</td>
<td>7.66</td>
<td>8.29</td>
<td>6.6</td>
<td><strong>10.68</strong></td>
<td>10.62</td>
<td><strong>10.44</strong></td>
</tr>
<tr>
<td>RF</td>
<td>5.70</td>
<td>6.68</td>
<td>5.14</td>
<td>6.85</td>
<td>9.28</td>
<td>8.31</td>
</tr>
<tr>
<td>CO</td>
<td>0.04</td>
<td>0.07</td>
<td>0.07</td>
<td></td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>Polynomial</td>
<td>0.04</td>
<td>0.07</td>
<td>0.07</td>
<td>N/A</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>RF</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td></td>
<td>0.02</td>
<td>0.05</td>
</tr>
</tbody>
</table>
However, our findings indicate that their performance varied by location, highlighting the benefits of multiple location deployment during sensor evaluation.

Table 6: Results of NO₂ and O₃ LCAQ sensors tested by AQ-SPEC (only electrochemical type sensors are included, data retrieved on March 5th, 2022)

<table>
<thead>
<tr>
<th>Make (Model)</th>
<th>Pollutant</th>
<th>Field R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>APIS</td>
<td>NO₂</td>
<td>0.30 to 0.44</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.73 to 0.83</td>
</tr>
<tr>
<td>AQMesh (v4.0)</td>
<td>NO₂</td>
<td>0.0 to 0.46</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.46 to 0.83</td>
</tr>
<tr>
<td>AQMesh (v5.1)</td>
<td>NO₂</td>
<td>0.49 to 0.54</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.62 to 0.74</td>
</tr>
<tr>
<td>Igienair (Zaack AQI)</td>
<td>NO₂</td>
<td>0.53 to 0.58</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.0</td>
</tr>
<tr>
<td>Kunak</td>
<td>NO₂</td>
<td>0.24 to 0.32</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.86 to 0.88</td>
</tr>
<tr>
<td>Magnasci SRL</td>
<td>NO₂</td>
<td>0.00 to 0.05</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.00 to 0.08</td>
</tr>
<tr>
<td>Oizom (Polludrone Smart)</td>
<td>NO₂</td>
<td>0.002 to 0.03</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.14 to 0.23</td>
</tr>
<tr>
<td>Perkin Elmer (ELM)</td>
<td>NO₂</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.89 to 0.96</td>
</tr>
<tr>
<td>Spec Sensors</td>
<td>NO₂</td>
<td>0.0 to 0.16</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.0 to 0.24</td>
</tr>
<tr>
<td>Vaisala (AQT410) Ver. 1.11</td>
<td>NO₂</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.40 to 0.58</td>
</tr>
<tr>
<td>Vaisala (AQT410) Ver. 1.15</td>
<td>NO₂</td>
<td>0.43 to 0.61</td>
</tr>
<tr>
<td></td>
<td>O₃</td>
<td>0.66 to 0.82</td>
</tr>
</tbody>
</table>

2.4.2 Impact of CO Data on NO₂ and O₃ Sensor Performances

After CO sensor signal (voltage) was included as an independent variable in the three calibration models for NO₂ and O₃ sensors, the performances of calibration models generally increased (Table 7 for $R^2$ and Table 8 for RMSE). This finding is consistent for both NO₂ and O₃, primarily when the original calibration model (without CO data) performs poorly. With included CO data,
the mean linear $R^2$ values were improved by 24% from 0.59 to 0.72 for NO$_2$ and 28% from 0.64 to 0.81 for O$_3$ across all sites. The mean RMSE values for the linear method were reduced by 17% for NO$_2$ and 21% for O$_3$. The inclusion of CO data works well at New York for O$_3$ (linear $R^2$ values increased from 0.23 to 0.7, RMSE reduced by 38%), at Riverside for NO$_2$ (Linear $R^2$ increased from 0.26 to 0.59, RMSE reduced by 26%), at Phoenix for both NO$_2$ and O$_3$, and at Sacramento for O$_3$. Similar findings were also observed when using polynomial and RF calibration methods.

Table 7: Sensor performance ($R^2$) at corresponding cities, with CO data introduced as an independent variable. Data shown in parentheses are changes of $R^2$ value when CO data were included in the model. Substantial improvements ($R^2$ improvements $\geq +0.2$) are bolded

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Portland</th>
<th>Atlanta</th>
<th>Riverside</th>
<th>Sacramento</th>
<th>New York</th>
<th>Phoenix</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO$_2$</td>
<td>Linear</td>
<td>0.80(+0.07)</td>
<td>0.45(+0.11)</td>
<td>0.59(+0.33)</td>
<td>0.89(+0.06)</td>
<td>0.86(+0.02)</td>
</tr>
<tr>
<td></td>
<td>Polynomial</td>
<td>0.84(+0.01)</td>
<td>0.45(+0.08)</td>
<td>0.48(+0.28)</td>
<td>0.89(+0.01)</td>
<td>0.85(-0.03)</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.86(+0.02)</td>
<td>0.74(+0.09)</td>
<td>0.68(+0.2)</td>
<td>0.97(+0.04)</td>
<td>0.92(+0.02)</td>
</tr>
<tr>
<td>O$_3$</td>
<td>Linear</td>
<td>0.78(+0.15)</td>
<td>0.83(+0.02)</td>
<td>0.97(+0)</td>
<td>0.80(+0.21)</td>
<td>0.70(+0.47)</td>
</tr>
<tr>
<td></td>
<td>Polynomial</td>
<td>0.77(+0.12)</td>
<td>0.77(-0.02)</td>
<td>0.95(+0)</td>
<td>0.76(+0.21)</td>
<td>0.60(+0.42)</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.93(+0.12)</td>
<td>0.89(+0.03)</td>
<td>0.97(+0)</td>
<td>0.94(+0.12)</td>
<td>0.81(+0.42)</td>
</tr>
</tbody>
</table>

Table 8: Sensor performance (RMSE) at corresponding cities, with CO data introduced as an independent variable. Data shown in parentheses are changes of RMSE when CO data were included

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Portland</th>
<th>Atlanta</th>
<th>Riverside</th>
<th>Sacramento</th>
<th>New York</th>
<th>Phoenix</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO$_2$</td>
<td>Linear</td>
<td>2.99(-0.49)</td>
<td>3.92(-0.37)</td>
<td>3.25(-1.14)</td>
<td>4.89(-1.1)</td>
<td>4.07(-0.3)</td>
</tr>
<tr>
<td></td>
<td>Polynomial</td>
<td>2.69(-0.09)</td>
<td>3.93(-0.26)</td>
<td>3.66(-0.9)</td>
<td>4.92(-0.17)</td>
<td>4.21(0.47)</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>2.52(-0.2)</td>
<td>2.76(-0.4)</td>
<td>2.94(-0.81)</td>
<td>2.37(-1.54)</td>
<td>3.04(-0.39)</td>
</tr>
<tr>
<td>O$_3$</td>
<td>Linear</td>
<td>6.02(-1.82)</td>
<td>7.34(-0.46)</td>
<td>5.54(-0.11)</td>
<td>7.02(-3.16)</td>
<td>6.4(-3.92)</td>
</tr>
<tr>
<td></td>
<td>Polynomial</td>
<td>6.4(-1.26)</td>
<td>8.62(0.33)</td>
<td>6.96(0.36)</td>
<td>7.8(-2.88)</td>
<td>7.43(-3.19)</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>3.42(-2.28)</td>
<td>6.17(-0.51)</td>
<td>4.97(-0.17)</td>
<td>3.96(-2.89)</td>
<td>5.14(-4.14)</td>
</tr>
</tbody>
</table>
The improved model performances as a result of including CO data were included are primarily for three reasons: (1) correlated temporal variation patterns between CO and NO\textsubscript{2} and between CO and O\textsubscript{3} concentrations; (2) different performances of low-cost CO, NO\textsubscript{2}, and O\textsubscript{3} sensors; and (3) different impacts of environmental conditions on their performances. The rationale for the hypothesis is explained in the following paragraphs.

First, as shown in Table 9, the hourly concentrations of CO and NO\textsubscript{2} measured by co-located FRM/FEM instruments are moderate to relatively highly correlated in all cities. The highest $R^2$ values between CO and NO\textsubscript{2} are found at Riverside (0.79), followed by New York (0.72) and Phoenix (0.65). In these three cities, the temporal variations of CO are similar to those of NO\textsubscript{2}, likely due to similar emission sources. Examination of the 2017 National Emission Inventory (NEI) data suggests CO and NO\textsubscript{2} emissions at all three monitoring stations are dominated by on-road and non-road mobile sources (on average 75% for NO\textsubscript{2} and 87% for CO).

Second, correlations between measurement data collected by low-cost CO and NO\textsubscript{2} sensors differed across cities (Table 9). Such differences are likely due to the performance differences between low-cost CO and NO\textsubscript{2} sensors and the different impacts of environmental conditions on
their performances. In this study, electrochemical CO sensors used in the SCI-608 generally performed better than NO\textsubscript{2} sensors (Table 4 and Table 5), in part due to the NO\textsubscript{2} sensor design, which has room for improvement. (Farquhar et al., 2021) Additionally, AQ-SPEC (Collier-Oxandale et al., 2020) evaluated the field performance of LCAQ sensors from different manufacturers, which have both electrochemical NO\textsubscript{2} and CO sensors onboard. The averaged field $R^2$ values were between 0.59 and 0.66, with a maximum of 0.94 for CO. Meanwhile, the value for NO\textsubscript{2} was between 0.18 and 0.30, with a maximum of 0.58. Furthermore, the performance of low-cost electrochemical NO\textsubscript{2} sensors is known to degrade when the ambient temperature exceeds 30 °C but less so for the CO sensor. (Rogulski et al., 2022, Han et al., 2021 and Cross et al., 2017)

For these two reasons, a low-cost CO sensor may be able to capture temporal CO concentration variability reasonably. However, a low-cost NO\textsubscript{2} sensor may only capture a portion of the temporal NO\textsubscript{2} concentration variability or less at high temperatures. Since CO and NO\textsubscript{2} concentrations co-vary to some extent, a portion of the missing NO\textsubscript{2} concentration variability that was not captured by the low-cost NO\textsubscript{2} sensor is captured by the CO sensor. When we introduced the CO sensor as an independent variable in NO\textsubscript{2} calibration models, a portion of the missing NO\textsubscript{2} variability was reintroduced into the model, leading to better model performance. The NO\textsubscript{2} calibration model performance improved most in Riverside (summer deployment, mean and maximum temperatures of 26.9 and 44.2 °C), moderately in Phoenix (winter/spring deployment, mean and maximum temperatures of 15.7 and 34.3 °C), and minimum in New York (winter/spring deployment, mean and maximum temperatures of 7.5 and 23.9 °C). Ambient CO and NO\textsubscript{2} concentrations in Portland and Atlanta are not as well correlated (Table 9). Therefore, including CO data in the NO\textsubscript{2} calibration model was not as beneficial as in
Riverside. Similar phenomena were observed with improved O\textsubscript{3} calibration model performance when CO data were introduced as an independent variable. CO and O\textsubscript{3} concentrations measured by FRM/FEM instruments are moderately correlated in New York and Phoenix, but low-cost sensor measurements are not well correlated due potentially to sensor performance differences. The inclusion of CO data in the O\textsubscript{3} calibration model may reintroduce some missing temporal O\textsubscript{3} concentration variability not captured by the O\textsubscript{3} signal from the sensor but captured by the CO sensor, thus leading to improved model performance. Impacts of environmental conditions on the performance of the O\textsubscript{3} sensor are not as substantial as those for the NO\textsubscript{2} sensor. In the SCI-608 monitor, two onboard electrochemical sensors were used for O\textsubscript{3} measurement. The first one measured NO\textsubscript{2} and O\textsubscript{3} (as NO\textsubscript{2} + O\textsubscript{3}), and the second sensor measured only NO\textsubscript{2}. The two sensors are fundamentally similar, but an O\textsubscript{3} removal apparatus is installed on the second sensor, so it does not respond to O\textsubscript{3}. Naturally, environmental conditions that impact the NO\textsubscript{2} sensor will also affect the O\textsubscript{3} + NO\textsubscript{2} sensor. However, their impacts were mostly canceled out when subtracting the NO\textsubscript{2} sensor signal from the O\textsubscript{3} + NO\textsubscript{2} sensor signal to obtain the O\textsubscript{3} signal.

Overall, our findings suggest that the signals from the onboard CO sensor may benefit NO\textsubscript{2} and O\textsubscript{3} sensor calibration, provided that CO and NO\textsubscript{2} and CO and O\textsubscript{3} concentrations are at least moderately correlated. It is worth mentioning that this study is not the first one that integrated the CO signal for the calibration of other sensors. For example, Cross et al., explored using signals from CO, CO\textsubscript{2}, NO, NO\textsubscript{2}, and total oxidant (O\textsubscript{x}) sensors to calibrate the NO sensor in the high-dimensional model representation method. To our knowledge, this study is the first that systematically investigated the mechanisms behind the calibration method. The presented method is intuitive and easy to implement and has great potential to improve the performances of selected LCAQ sensors.
2.4.3 Study Limitation

This study does have several limitations. First, electrochemical sensors are known to respond to interfering gases, which will lead to worse sensor performance relative to a gold standard method; it is likely that varying amounts of interfering gases existed at the six monitoring stations during the study.

However, without detailed measurement data, it is difficult to quantify the impact of interfering gases on the low-cost sensors deployed in this study. Second, due mostly to logistics, the deployments of all SCI-608 monitors did not occur at the same time, making a direct comparison across all six locations difficult. Third, due to length limitations, we focused our discussion on the coefficient of determination ($R^2$) and root mean square error (RMSE), which is not the ideal metric for comparing sensor performance across cities with varying pollution levels. For example, $R^2$ values are expected to be higher at locations with a wider range of concentrations. Including more metrics, such as mean absolute error or mean fractional error, would be more indicative of model performances. We nonetheless still choose to use $R^2$ because it is suitable for quantifying how much temporal pollution concentration variability is captured by the model.

Fourth, we only used uncorrected voltage data collected from working and reference electrodes in this study as we do not have voltage data from other electrodes (e.g., auxiliary) readily available. If such additional data were to be used, the performances of calibration models are expected to be improved. However, we do not anticipate the conclusions of this study to be changed by excluding additional voltage data. The previous study also showed that the auxiliary electrode in Alphasense electrochemical sensors did not function as desired. (Cross et al., 2017)
2.5 Summary and Conclusion

Six LCAQ sensors were deployed in six cities with diverse meteorological conditions across the U.S. to evaluate their performance using three different methods. We found that the performance of low-cost NO₂ and O₃ sensors varied among cities. The performance of calibration models generally improved (considerably in certain cities) when the signals from CO sensors were included. Such observations can be explained by (1) the temporal co-variation of CO and NO₂ and CO and O₃ concentrations; (2) different performance levels of CO, NO₂, and O₃ sensors; and (3) different impacts of environmental conditions on low-cost sensors. Low-cost electrochemical CO sensors performed better than NO₂ and O₃ sensors, particularly under high temperature and humidity conditions. Because CO and NO₂ and CO and O₃ concentrations co-vary to some extent, the temporal CO concentration variations captured by the CO sensor reflected the temporal NO₂ concentration variability. When signals from the low-cost CO sensor were included in calibration models for NO₂ and O₃ sensors, a portion of the temporal concentration variability not captured by NO₂ and O₃ sensors may have been reintroduced into the calibration model, thus leading to better model performances. However, such improvements are expected to vary among locations. To our best knowledge, this phenomenon has not been reported previously, and other researchers can use our findings to improve the performance of low-cost NO₂ and O₃ sensors.
CHAPTER 3: PERFORMANCE COMPARISON OF LOW-COST SENSOR CALIBRATION MODEL AMONG SIX US CITIES

3.1 Introduction

Low-cost air quality monitoring instruments that are being designed with the application of the Internet of Things (IoT) is getting popular both in the academic and industrial research sectors as those sensors are lightweight, inexpensive, and easy to install and maintain. (Chojer et al., 2020) The Federal Reference Instruments (FRM) and Federal Equivalent Instruments (FEM) that are used in the air quality monitoring field for both monitoring ambient air and preparing government policies are known to provide near accurate data, but these sensors are very expensive to be owned by individual level. (Hall et al., 2014) High spatio-temporal resolution of pollutant concentration data cannot be achieved by using solely the FRM and FEM instruments. That is why these IoT-powered low-cost sensors are being used to get high-resolution pollutant concentrations. But these sensors come with several disadvantages related to data accuracy, inter-sensor variability (Polidori et al., 2016, Mead et al., 2013 and Popoola et al., 2018), weather-related vulnerability (Popoola et al., 2016 and Budde et al., 2018), long-term stability (Popoola et al., 2016 and Budde et al., 2018) and cross-sensitivity (Hossain et al., 2016, Maag et al., 2016 and Lewis et al., 2016). The performance of those sensors could be different in different parts of the world. Their performance could be even varied in different parts of a country with heterogenous weather conditions. The concentration value derived from the electrical parameters (voltages and currents) of these sensors is far from the ground truth FRM value and needs
calibration. (Hagan et al., 2018) Calibrations have been performed by co-locating LCAQ sensors with FEM/FRM instruments and then using the concentrations of those FRM/FEM instruments as a ground truth number. Different calibration methods (e.g., Multivariate linear regression, Support Vector Machine, Long Short term Memory and Decision Tree) have been tested previously in the field of LCS. None of the studies investigated large-scale calibration analysis with their sensors in different cities or countries with a variety of environmental conditions.

This part of the study will investigate the performance of LCAQ sensors in different cities of the continental United States with heterogenous weather conditions. This includes comparing the performance of the sensors (NO₂, O₃ and PM₂.₅) in local conditions against when calibrated in a different region. Also, it will compare the performance of LCAQ sensors in the winter and non-winter seasons of the same city and in different temperature and relative humidity combination (High, Medium, Low).

3.2 Data Collection and Method

The raw signals from the PM₂.₅, CO, O₃, and NO₂ were collected from the SCI-608 monitor that houses multiple sensors designed for Particulate Matter (PM) and gaseous pollutants. Optical Particle Counter (OPC) was used to get the PM signal and electrochemical sensors were used to get the signals for gaseous pollutants. The monitor was powered using AC power source. The data that was measured was transferred by a wireless cellular network to a central server for data analysis and visualization purposes. The data was collected from 6 regulatory monitoring sites in 6 different cities (Portland, OR; Atlanta, GA; Riverside, CA; Sacramento, CA; New York City, NY; and Phoenix, AZ) in the continental United States.
Figure 3 shows the boxplot with temperature, relative humidity, NO₂, O₃ and PM₂.₅ concentrations data range across all the cities. PM₂.₅ is showing the upper outlier data across all the cities with extreme outliers found in Phoenix, AZ (Maximum concentration = 250 µg/m³). O₃ concentrations were shown more stability with no outliers in Atlanta, Phoenix, Riverside and Sacramento. New York City has both upper and lower bound temperature outliers showing extreme weather condition during the sampling period. Overall, New York City and Portland is showing highest number of outliers. On the other hand, Atlanta, Sacramento and Riverside showing relatively low number of outliers across all the parameters.

For calibration of the sensors, linear, third order polynomial and random forest models were used. More details of the data collection and methodology are provided in section 2.3.
3.3 Result and Discussion

3.3.1 Comparison between Local Calibration and Calibration in another region

Local calibration across all the regions was observed with higher accuracy for NO\textsubscript{2} measurement than calibration in another region across most of the locations analyzed. The right diagonal values in Figures 4 and 5 are showing the calibration values (R\textsuperscript{2} and RMSE) for local calibration. The horizontal axis of the heatmaps is the locations where the model is being trained and the vertical axis is the locations where the model has been tested. If the R\textsuperscript{2} parameter is considered (Figure 4), there are some places where local calibration is providing lower accuracy than calibration in other region (e.g., Portland local calibration for linear regression is observed with less accuracy (R\textsuperscript{2} = 0.73) than Portland calibration in New York (R\textsuperscript{2} = 0.83) and Sacramento (R\textsuperscript{2} = 0.81)). Sacramento region is showing a better correlation value than other regions regardless of the region the model has been trained. On the other hand, Riverside is showing the worst correlation coefficient for both the training and test sets regardless of the region the model has been trained or tested. The lower correlation parameter in Riverside can be associated with being the region with the lowest days of data available (20 days) among the six cities and has the narrowest range of NO\textsubscript{2} concentration window (2-31 ppbv) (Figure 3). The median NO\textsubscript{2} concentration is also lowest in Riverside (Figure 3). If the RMSE parameter is considered (Figure 5), for almost all the locations (except PHX-ATL, SAC-PTL for Linear and Polynomial regression, and PHX-ATL and PHX-PTL for Random Forest) the local calibration is observed with less RMSE than calibration in another region. It varies from 2.72 ppbv (PTL local RF) to 30.84 ppbv (PTL-RAV Polynomial). Portland resulted with the lowest RMSE data among the six cities considering the difference between local calibration because Portland has the highest sample size (301 days). That could be a reason behind the good model performance in Portland. Phoenix had the highest mean NO\textsubscript{2}
concentration among the six cities and came out to be the worst performer in the perspective of RMSE (7.51 ppbv for linear regression, 6.86 ppbv for polynomial regression, and 5.46 ppbv for random forest).

For O$_3$, if the R$^2$ parameter is considered, local calibration is not providing better accuracy in New York. Apart from that, all the other locations local calibration is showing better accuracy for O$_3$ calibration. Riverside is showing unexpectedly high accuracy for local calibrations and non-local calibrations (Figure 6). Riverside’s highest mean O$_3$ concentrations (42.1 ppbv) could be associated with its high model R$^2$ performance. Riverside’s median and third quartile value for O$_3$ concentration is also showing higher than the rest 5 locations (Figure 3) that could validate the relatively higher R$^2$ in Riverside. If considered as a basis of RMSE (Figure 7), the local calibration is providing less RMSE than the calibration in other regions. Riverside’s local calibration RMSE is the lowest (5.65 ppbv for linear, 6.6 ppbv for polynomial and 5.14 ppbv for
random forest) among the six regions and New York City is the highest (10.32 ppbv for linear, 10.62 ppbv for polynomial and 9.28 ppbv for random forest).

![Accuracy (R²) of electrochemical O₃ sensors](image1)

Figure 6: Accuracy (R²) of electrochemical O₃ sensors

For PM₂.₅ R² and RMSE (Figures 8 and 9), local calibration is generally providing better accuracy than most of the other regions observed with some minor exceptions in Atlanta and Riverside.

Portland local calibration and calibration in other regions are showing a very low level of model performance (R²) due to its lowest mean PM₂.₅ concentrations (5.95 µg/m³). Extremely high RMSE (42590 µg/m³ to 60690 µg/m³) was observed for Portland’s polynomial non-local based regression which can be addressed by a higher PM₂.₅ concentration that if calibrated with a third-degree exponential should have a higher RMSE.

The higher accuracy in the local calibration can be due to the varying environmental condition across different cities. Different cities also have different particle size distributions of pollutants and emission sources are also different. For example, Riverside and Sacramento emissions can be
attributed to wildfire and prescribed fire. On the other hand, New York emissions can be attributed to on-road mobile source emissions. Before installing an SCI-608 sensor in a particular region, local calibration needs to be executed.

![Figure 8: Accuracy ($R^2$) of Particle Sensors](image)

![Figure 9: RMSE of Particle Sensors](image)

Across all the regions regardless of local calibration or calibration in other cities for sensors, the machine learning algorithm (Random Forest) that is tested is mostly observed with higher accuracy and less root mean squared error than the model which is calibrated with conventional mathematical regression (Linear regression and Polynomial regression). This implies a non-linear relationship between low-cost sensor response and reference concentration of pollutants.

### 3.3.2 Seasonal impact on the performance of low-cost sensors

Four out of the six cities that were investigated have the data available for both winter and non-winter (Fall for Sacramento and Summer for New York, Portland, and Phoenix) seasons. Across the four cities, 15 days of data (First 15 days for New York, Portland and Phoenix and last 15 days for Sacramento) were considered winter concentration data and another 15 days (Last 15
days for New York, Portland and Phoenix and first 15 days for Sacramento) of data were considered non-winter data for the synchronization purpose. Across all the four cities, the winter calibration was observed with better accuracy (0.94 for Portland, 0.91 for Sacramento, 0.95 for New York, and 0.55 for Phoenix) than a non-winter calibration (0.76 for Portland, 0.81 for Sacramento, 0.73 for New York and 0.48 for Phoenix) for NO₂ (Figure 10). Linear regression is the only calibration method that was used in all the cities. Figure 10 also showed the scatter plots showing predicted NO₂ concentrations (From SCI-608 sensor signal) against observed concentrations (From FRM/FEM sensor) with a 1:1 line for NO₂ concentrations for both winter and non-winter seasons of the year. High FRM/FEM concentrations in the winter season were observed from the scatter plots for all the four cities. That is because NO₂ is a primary pollutant emitted directly from the source. The main source of NO₂ is the vehicular tailpipe emission and emissions from the power plant. As the winter season has low temperature and humidity, the cold start for vehicles is common in New York, Phoenix, and Portland where the temperature is negative to 0°C. Vehicle idling and industrial point sources in the wintertime produce an elevated amount of NO₂. Higher actual and predicted concentrations were responsible for better winter performance of calibration models for NO₂. Negative concentrations were observed in calibrating

**Figure 10:** Accuracy (R²) and the scatter plots across Winter and Non-winter period (NO₂)
the low-cost SCI-608 sensors across the cities when the actual FRM/FEM concentrations were low (<10 ppbv).

For O\textsubscript{3} sensors, winter preference was observed in Portland (0.66 in Winter and 0.64 in Non-Winter), Sacramento (0.67 in Winter and 0.59 in Non-winter), and New York (0.45 in Winter and 0.26 in Non-winter) but not in Phoenix (0.39 in Winter and 0.69 in non-winter) (Figure 11). The Scatter plot of Figure 11 also showed relatively high O\textsubscript{3} concentrations (for both predicted and actual data) for the non-winter period in Phoenix. Higher concentrations are associated with higher R\textsuperscript{2} values for non-winter Phoenix data. It was observed with a relatively high concentration of O\textsubscript{3} data in the non-winter period as O\textsubscript{3} is formed in the air with photochemical reaction in presence of sunlight. As there is not enough sunlight available to form O\textsubscript{3} in wintertime across all the regions, O\textsubscript{3} concentrations were found lower across all four cities in winter. Negative O\textsubscript{3} concentrations were predicted where observed concentrations were close to 0 ppbv.

![Figure 11: Accuracy (R\textsuperscript{2}) and the scatter plots across Winter and Non-winter period (O\textsubscript{3})](image)

For PM sensors, winter preference was observed in all the cities investigated. (Figure 12). Higher coefficient of determination values was observed in Portland (0.16 for winter and 0.12 for non-winter), Sacramento (0.73 for winter and 0.63 for non-winter), New York City (0.94 for winter and 0.87 for non-winter), and Phoenix (0.96 for winter and 0.59 for non-winter). Portland has the
overall lowest mean PM concentration (5.95 µg/m^3). As discussed in the previous sections, the linear calibration model in our study did not perform quite satisfactory in low concentration. That could be the reason that Portland sensors were showing less correlation of coefficient for both winter and non-winter regions than sensors in the rest three locations. Overall, from Figure 12 scatter plots, it could be observed that winter season PM_{2.5} concentration is higher than non-winter season across all the four cities. For the winter season with dry weather and less humidity across the regions, the fine particles cannot be deposited on the ground and tend to remain suspended in the air is one of the reasons that winter concentration of PM_{2.5} is higher and as a result calibration performance in winter is observed to be better.

![Figure 12: Accuracy (R^2) and the scatter plots across Winter and Non-winter period (PM_{2.5})](image)

### 3.3.3 Effect of Temperature and Relative Humidity in the Sensor Performance

To investigate more the seasonal impact of electrochemical sensors and optical particle counters, the temperature, and relative humidity impact were investigated in the four cities where both the winter and non-winter data were available. Up to the 25th percentile of temperature and relative humidity was tagged as ‘Low’, 25th to 75th percentile of temperature and relative humidity was tagged as ‘Medium’, above 75th percentile of temperature and relative humidity was tagged as ‘High’. It was observed that low-temperature accuracy across all four cities for NO_{2} sensors was...
higher than the medium and high-temperature accuracy (Figure 13). For New York, the low-temperature $R^2$ varies from 0.88-0.96, for Phoenix it is 0.69-0.84, for Portland it is 0.88-0.95 and for Sacramento, it is 0.95-0.96. The low $R^2$ in Phoenix can be traced back to Figure 10 where it was observed that Phoenix had lower NO$_2$ concentration in both winter and non-winter seasons than three other regions. That is why the $R^2$ values for Phoenix in high temperatures were also poor (0.1-0.15). For the rest three regions, the high temperature was showing lesser values of $R^2$ than medium and low temperature because concentrations of NO$_2$ in high temperatures were considerably higher. (Figure 10) Based on RMSE (Figure 13), the low-temperature RMSE in all the four regions was observed generally lower than medium and high-temperature RMSE. For example, in New York City, the low-temperature RMSE ranges from 1.9-3.2 ppbv but the medium and high-temperature RMSE ranges from 2.97-4.36 ppbv and 3.04-4.41 ppbv.

![Figure 13: Accuracy ($R^2$) (Top) and RMSE (Bottom) based on temperature and relative humidity for NO$_2$](image)

The probable reason is that the electrochemical NO$_2$ sensor performance tends to degrade in high temperatures (>30°C) but there is no evidence that shows the impact of humidity on NO$_2$ sensors. The significant impact of relative humidity on the accuracy of NO$_2$ sensors was not observed.
For O₃ sensors, temperature effect cannot be concluded as New York and Sacramento are showing better accuracy in high temperatures, on the other hand, Portland is showing better performance in low temperature. Phoenix is not showing any preference for either temperature or relative humidity gradients. O₃ is a complicated pollutant to explain this scenario. It is expected that O₃ concentration to stay lower in the winter season across all the regions. Despite expectation for low-temperature preference for O₃, low-temperature accuracy cannot be concluded here.

![Figure 14: Accuracy (R²) (Top) and RMSE (Bottom) based on temperature and relative humidity for O₃](image)

There could be a correlation between the O₃ sensor performance and relative humidity gradient. From Figure 14, the effect on evaluation metrics between low and high humidity still was not convincing to conclude that O₃ sensor performance had been affected by relative humidity. From this study, it is concluded that it is crucial to keep both the temperature and relative humidity parameters in the O₃ calibration model, but it is not required to include RH in NO₂ calibration models.
For Particle sensors, the positive effect of low temperature is clearly visible in the four cities investigated (Figure 15). The $R^2$ range in low temperature for New York was 0.95-0.99 and for high temperature it was 0.79-0.99. For Phoenix, Portland and Sacramento the $R^2$ range were 0.82-0.98, 0.91-0.98 and 0.82-0.86 in low temperature and 0.19-0.66, 0.95-0.98 and 0.49-0.73 in high temperature. It was showed in Figure 12 that PM$_{2.5}$ concentration was higher in the winter season because of lack of rainfall and the effect of wind and wildfire. High concentration can be associated with a higher correlation coefficient, but the model did not perform satisfactorily in lower temperatures based on RMSE (Figure 15). For example, New York City RMSE range in high temperature was 0.24-0.54 $\mu$g/m$^3$ and for low temperature, it was 0.81-1.66 $\mu$g/m$^3$. Relative humidity effect was not observed in the PM sensors as different location showing performance preference in different relative humidity bracket (New York and Portland in low, Phoenix and Sacramento in high).

Figure 15: Accuracy ($R^2$) (Top) and RMSE (Bottom) based on temperature and relative humidity for PM$_{2.5}$

3.4 Summary and Conclusion

This study investigated different calibration methods in the low-cost electrochemical and OPC air quality sensors. An increase in accuracy in low temperatures for NO$_2$ and PM$_{2.5}$ were observed as
low-cost sensor performance is negatively impacted in high-temperature conditions. Local calibration showed better accuracy in LCAQ sensors across most of the locations. There are several limitations to this study. First, the data was collected in different periods in different cities because of logistic reasons mainly due to site accessibility and availability. Second, different sites show different local calibration accuracy even if using the same FRM/FEM and low-cost sensors. One reason could be the different weather conditions and difference in types of pollution sources of different places that are affecting the performance of those sensors. Third, only linear regression methods were used in determining the seasonal impact and impact of calibration in high, medium, and low temperature and relative humidity condition. Fourth, only random forest was used as a representative machine learning method. Other ensemble decision tree models, support vector machine models, nearest neighbor models or neural network models could be tested for sensor calibration. Overall, this study showed the importance of regular calibration of LCAQ sensors in local condition against ground FRM/FEM measurement. Long term seasonal calibration also found important for the accuracy of LCAQ sensors.
CHAPTER 4: CONCLUSION

Using LCAQ sensors for ambient air quality measurement have gained tremendous popularity in the past decade. Many earlier research (Patton et al., 2022, Datta et al., 2020, Zaidan et al., 2020, Zimmerman, 2017, Topalović et al., 2019, Lim et al., 2019, Johnson et al., 2018 and De Vito et al., 2018) have studied LCAQ sensor calibration using multiple methodologies under both controlled laboratories and field conditions, with better performances often found under lab conditions. Under field conditions, calibration model’s performances can vary among different site locations as factors such as pollutant sources, meteorology, and atmospheric chemistry are likely to be not the same among different cities. (De Vito et al., 2020)

For research-grade equipment to pass FRM/FEM certification processes their equipment performances need to be extensively evaluated at four US locations with distinct climatological conditions with strict testing protocols. (EPA, 1997) For example, an equipment manufacturer may choose the first location to be at LA basin or CA central valley with high PM$_{2.5}$ and particle nitrates contents; the second location may be at a western city such as Denver or Salt Lake City with higher elevation, cold weather, and high wind and dust; the third location may be midwestern city (e.g., Chicago, Indianapolis, Columbus and Detroit) and the last one could be a northeastern or mid-Atlantic city (e.g., New York City, Philadelphia, Washington D.C. or Boston).

For LCAQ sensor, however, such rigorous evaluations at multiple locations were rarely performed. AQ-SPEC under South Coast Air Quality Management District uses strict
protocols to evaluate the performance of many commercial LCAQ sensors but only at one reference site locations in Southern California. (Papapostolou et al., 2017, Feenstra et al., 2019 and Collier-Oxandale et al., 2020) Often, a manufacturer develops a calibration model at one location and apply the same calibration model to estimate pollutant concentration regardless of locations, despite that previous studies have shown a widely varied sensor performance among different locations, due not only to changing local weather conditions, but also to other factors such as known cross-sensitivity of electrochemical gas sensors. (Feenstra et al., 2019 and Cross et al., 2017)

This research was conducted to investigate the potentially varying performances of LCAQ sensors (Sailbri Cooper SCI-608) among six cities in the US. An unexpected performance improvement when using signals from CO sensors to calibrate NO\textsubscript{2} and O\textsubscript{3} sensors were discovered and potential reasons for such findings were also investigated. The study investigated multiple methodologies (linear calibration, 3\textsuperscript{rd} order polynomial calibration, and RF) for low-cost air quality sensor calibration across six cities (Atlanta, Portland, Riverside, Sacramento, New York City, and Phoenix) in the United States. The data for this study is collected from April 2019 to April 2020 across the six different cities. It was observed that local calibration provides better accuracy than adopting calibration equation developed in other regions. This finding is true across most of the models and pollutants tested. Also, if signals from CO sensors were to be included in the calibration models of NO\textsubscript{2} and O\textsubscript{3}, model performance increases across all the regions and all the models tested. CO concentration found temporally co-vary with NO\textsubscript{2} and O\textsubscript{3} but the CO electrochemical sensor performance was found better than NO\textsubscript{2} and O\textsubscript{3} sensor especially NO\textsubscript{2} sensor. As a result, a portion of NO\textsubscript{2} and O\textsubscript{3} temporal variation can be captured and reintroduced in the calibration model if CO sensor signal is incorporated into the model. We
investigated the effect of temperature and relative humidity on the performance of the linear calibration model across four of the six cities where both winter and non-winter data were available. It was found that the performance of low-cost sensors (both electrochemical and Optical Particle Counter) in the winter season is better than in the non-winter season (late Summer or Early Fall). Furthermore, we also compared the performance of LCAQ sensors under different temperature and relative humidity (High, Medium, and Low) conditions. Best performances were found for low temperature conditions for NO₂ and PM₂.5 sensor. On the other hand, no substantial temperature impacts were observed for O₃ sensors.

Overall, this research provides valuable insights into LCAQ sensor’s calibration methodology across cities with substantially different environmental conditions. The results can be used to inform sensor manufactures, and policymakers for the design and deployment of future sensor network to better capture spatial variabilities of pollutant concentrations.
Figure 16: Time-series plot of hourly NO$_2$ concentrations at Portland as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration

Figure 17: Time-series plot of hourly NO$_2$ concentrations at Atlanta as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration

Figure 18: Time-series plot of hourly NO$_2$ concentrations at Riverside as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration
Figure 19: Time-series plot of hourly NO$_2$ concentrations at Sacramento as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration.

Figure 20: Time-series plot of hourly NO$_2$ concentrations at New York City as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration.

Figure 21: Time-series plot of hourly NO$_2$ concentrations at Phoenix as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration.
**Figure 22:** Time-series plot of hourly O$_3$ concentrations at Portland as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration

**Figure 23:** Time-series plot of hourly O$_3$ concentrations at Atlanta as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration

**Figure 24:** Time-series plot of hourly O$_3$ concentrations at Riverside as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration
Figure 25: Time-series plot of hourly \( O_3 \) concentrations at Sacramento as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration

Figure 26: Time-series plot of hourly \( O_3 \) concentrations at New York City as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration

Figure 27: Time-series plot of hourly \( O_3 \) concentrations at Phoenix as collected by FRM/FEM equipment, and from low-cost sensors with linear, polynomial, and random forest calibration
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