REAL-TIME AIR QUALITY MEASUREMENTS USING MOBILE PLATFORMS

BY PARVEEN SEVUSU

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ABSTRACT OF THE THESIS

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By PARVEEN SEVUSU

Thesis Director: Liviu Iftode

Air pollution poses a serious threat to our health and quality of life. Measuring pollution in the air we breathe and sharing the results with our peers is an important step in increasing social awareness for creating a clean environment. Usually, pollution measurements are conducted using expensive monitors at fixed locations. These measurements fail to provide accurate real-time pollution information in most of the highly polluted roads. It is desirable to have access to real time fine-grained measurements to be able to quickly analyze and identify alarming levels of pollutants.

Pervasiveness of smart phones with internet connectivity and increased availability of personal air quality sensors provide a unique opportunity to develop air pollution conscious community of users for collecting and sharing real time air pollution data. In this thesis, we propose air quality monitoring through mobile sensors, which are low-power, low-cost, designed to sample air pollutants such as carbon mono-oxide, nitrogen oxide, sulphur dioxide, environmental temperature, humidity and air pressure and communicate via Bluetooth with a smartphone. We built an iOS mobile application that makes use of location services available on the mobile phones, to record GPS co-ordinates along with air pollution readings. We built a mobile to cloud replication model, data exchange protocol and outlier detection for anomalous sensor readings. We also employed spatial database queries to optimize location based pollution data sharing and visualization of pollution data overlays on mobile map displays. We evaluated our mobile pollution-sensing model against stationary NJ DEP monitor and studied spatial granularity of

pollution data.

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Dedication

To my parents

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Chapter 1

Introduction

Air pollution is an important factor affecting the quality of the lives of millions. Most of the pollutants in the air are a result of emissions from cars, trucks, buses, factories, refineries and natural occurrences like volcanic eruptions and forest fires. Because people breathe in contaminated air, they are exposed to many health risks. Air pollution might cause cancer, premature death, developmental disorders to children, harm reproductive systems, result in asthma attacks, or cause lung cancer. It may also cause wheezing and coughing, shortness of breath, harm to cardiovascular system, increase susceptibility to infections, lung tissue redness, or swelling. US Federal laws like Clean Air Act are designed to control and regulate air pollution. It mandates Environmental Protection Agency (EPA) to enforce regulations to protect public from air pollution. Both at the federal and state level, various stationary air quality monitoring stations are setup at various urban and suburban locations to monitor air pollution. Air pollutants like sulfur dioxide (SO2), nitrogen dioxide (NO2), carbon monoxide (CO), ozone (O3), lead (Pb) and particulate matter (PM10) are continuously measured and monitored. The primary purpose of the data from these monitoring stations is to determine the air pollution level to which people are exposed and educate the public if unhealthy air pollution levels exist. But these monitoring stations cover only a small fraction of the whole populated area in the country.

Based on the motor vehicle registrations across states, the number of vehicles including cars and trucks on the roads increased by 30% in the last ten years [1]. Number of trucks alone almost doubled in the last ten years. On an average, a commuter spends more than fifty two minutes in travel per day (two way) and in some big cities he/she spends more than four hours per day (two way) inside the car [2]. According to US department of transportation, the total length of roads is four million miles and two hundred and forty six million vehicles travel on these roads [3]. Significant number of communities is built around these roadways. Motor vehicles emit a variety of gases such as Carbon Dioxide (CO_2), Carbon Monoxide (CO), Nitrogen Oxides (NO/NO_2), Particle Matter (PM10) and Ozone, which are by-products that come out of the exhaust systems. These emissions contribute significantly to the air pollution and smog especially in big cities. More than fifty three thousand people die per year because of these vehicular air pollutants [4].

Commuters encounter elevated levels of air pollution, especially Carbon Monoxide (CO) inside the car. Studies conducted by EPA shows that CO exposures while commuting in big cities like Denver, CO or Washington, DC, is three times higher than fixed stations monitor readings on CO levels [5]. Depending upon the traffic congestion, stop signs and weather conditions, the CO exposure inside the car is highly variable and some commuters are exposed to even higher levels of CO. There is a need for accurate real-time air pollution monitoring along the congested roadways and inside the car. Such real-time monitoring and sharing of air pollution information would educate commuters on the pollution levels that they are exposed to, and eventually propel the communities to develop policies and regulations to achieve a cleaner environment for us to breathe and live. ***In this thesis, we design a prototype that employs low cost air pollution sensors that interfaces with a mobile phone application to enable commuters on roadways to collect and share the air quality data inside the car with other commuters. This prototype would lay the foundation to build a social community of users that can monitor and share air quality data.***

1.1 Current State of Air quality monitoring

The Clean Air Act requires EPA to set Air Quality Standards for six criteria air pollutants commonly found in the US [6]. They are particulate matter, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides and lead.

Particulate matter (PM2.5/PM10): Particles can be divided into two major groups based on size, the bigger particles called PM10 (2.5 to 10 micrometers) and the smaller particles called PM2.5 (smaller than 2.5 micrometers). PM10 mainly constitutes dirt, dust and smoke from factories and roads, whereas PM2.5 comprises of metals and toxic organic compounds from automobiles and metal processing.

PM2.5, being lighter, can stay in the air longer and travel farther than PM10. When we breathe in air, any particles present in the air are also inhaled and easily travel into the respiratory system. Because PM2.5 is made up things that are more toxic (like heavy metals and carcinogenic organic compounds), PM2.5 can have worse health effects than the bigger PM10. Exposure to particulate matter leads to health effects such as asthma, coughing, wheezing, respiratory and cardiovascular morbidity and even lung cancer.

Ozone (O3): Ozone is found at ground level and in upper regions of the atmosphere. Oxides of Nitrogen (NO/NO2) reacting with volatile organic compounds (VOC) cause ozone at ground level. Warmer regions with increased traffic and industries generate higher levels of ground level ozone. Ozone, when inhaled, can irritate the airways, cause coughing and reduced lung capacity.

Carbon Monoxide (CO): The combustion cycles of gasoline in motor vehicles emit a poisonous, colorless and odorless gas. When humans breathe in CO, it blocks oxygen from reaching brain and heart and induce reduced oxygen-carrying capacity in the blood. Sometimes, excessive levels of carbon monoxide might even cause death.

Sulfur Dioxide (SO2): Motor vehicles and power plants emit SO2 when they burn sulfur-containing fuel like diesel. When inhaled, it causes respiratory ailments such as airways constriction and asthma symptoms.

Lead: Cars emit lead where unleaded gasoline is not used. Exposure to lead increases chances of stroke and heart attack and developmental disorders to children.

According to "The Global Burden of Diseases, Injuries, and Risk Factors Study for 2010" [7], outdoor air pollution contributed to 3.2 million deaths globally in 2010 up from eight hundred thousand just ten years ago. As the automobile usage in developing countries like India and China is growing at an increased pace, we expect the impact of air pollution on human health to get worse in near future.

With increasing concerns about impact of air pollution on health, EPA is required to monitor and assess air pollution levels across the country. There are around four thousand monitoring stations setup across US, which monitor air pollution as part of State and Local Air Monitoring Stations (SLAMS) network. For example in the state of New Jersey, there are nineteen stationary air-monitoring stations, out of which only six stations report carbon monoxide.

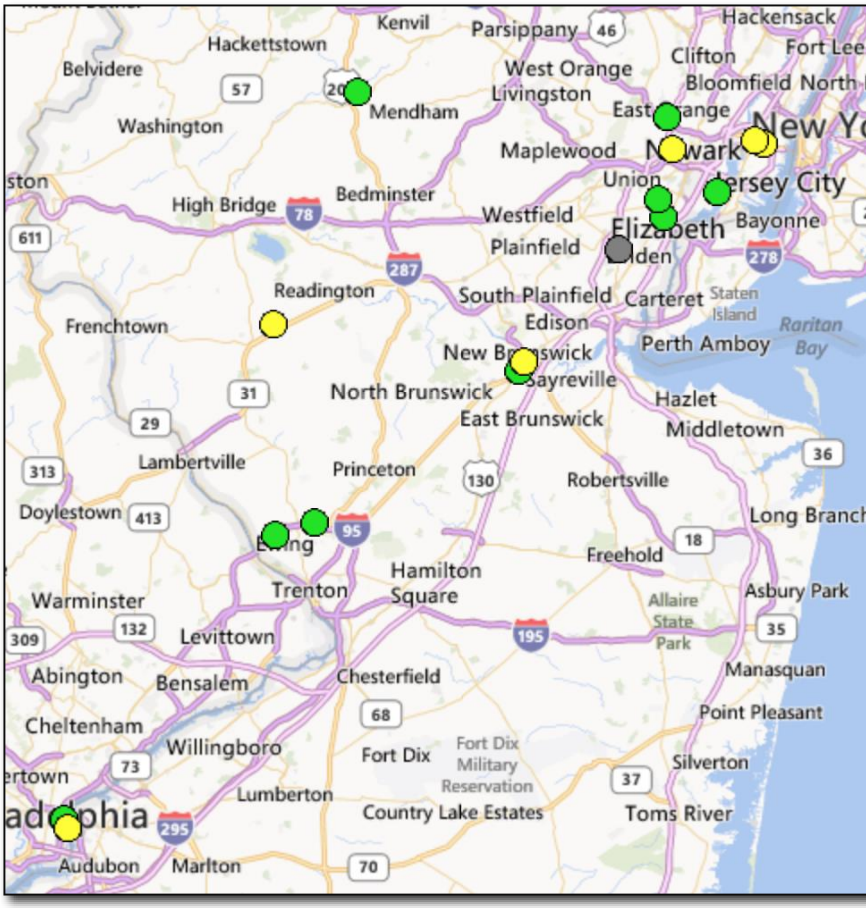


Figure 1-0-1 New Jersey Air Quality Monitoring Stations. Reprinted from http://www.njaqinow.net

Setting up a stationary air pollution monitoring system and maintenance of such stations is expensive and it involves a lot of maintenance overhead because air pollutants need to be sampled, measured, recorded, analyzed and shared over long periods and it needs to cover a significant geographical area. Usually such air pollution monitoring stations are located around areas of significant air pollution like industries and high population density areas like big cities. But the approach of having stationary, fixed air pollution monitoring stations has a serious limitation when we want to determine the level of the air pollution exposure outside of areas covered by these stations.

Various methods are employed at the stationary stations to measure air pollution. One of them is automatic sampling in which samples are measured real-time using chemical luminescence, UV fluorescence, IR absorption or Differential Optical Absorption Spectroscopy methods. The data is collected from various monitoring sites and recorded for further analysis. The other method is active sampling in which a known volume of air is pumped through a filter or chemical collector for a period of time and then sample is subjected to laboratory analysis. In general, the concentration of a pollutant in air can be estimated by measuring infrared absorption. But most of the time, the concentration of air pollutants is so low with the exception of carbon monoxide (CO), that such measurement techniques are not applied. Consequently, most of the air pollution measurement techniques involve removal of pollutant from the air by making use of nature of high rate of diffusion of gases in the air. The easiest way to separate them is pass the gases over a surface where one component of the air pollutant is removed or absorbed by chemical reaction into a non-volatile component that can be estimated by subsequent chemical analysis.

Air pollution changes are dynamic, changing almost every hour or even more often. Air samples and subsequent measurement of pollution simply give us a snapshot of an index of air pollution at a given time and given place. Even though various dispersion models can be used to estimate the concentration of air pollutants as they disperse away from the source of emission (e.g. cars and Trucks), such models depend on dynamic metrological data such as wind speed, temperature, rain/fog etc. and terrain data. Use of dispersion model is expensive for dynamic feedback to commuters and is of very limited value for an average commuter travelling by cars, on the road. The commuter would require an instrument, which continuously measures air pollutants and he/she would need to interpret the readings that is impractical and it is not economically scalable. So, we need an approach and model for measuring real-time air pollution levels at the locations travelled by a commuter and share this information with other people who do not possess air pollution monitors.

1.2 Need for Real-time Air Quality Information

In our thesis, we narrowed down our focus to the monitoring and sharing of Carbon Monoxide (CO) pollution levels. People need to be concerned about air pollution levels, especially those with respiratory disorders, heart problems and who have already been exposed to dangerous levels of air pollutants such as Carbon Monoxide (CO) need to watch for further exposure of air pollution. The side effects of air pollution is not reversible especially for Carbon Monoxide (CO), so if exposed to certain levels, we need to be vigilant about any additional exposure to reduce chances of any further health risks. Larger exposures of CO can lead to increased levels of toxicity in the nervous system, blood vessels and heart, which might result in eventual death. Higher air pollution levels irritate airways and induce asthma exacerbations. It would be really beneficial to such vulnerable group of people to have a real-time alert system that actively monitors air pollution levels and notify users of dangerous exposures of air toxics. Most of us assume that the enforcement of motor vehicle catalytic convertors helps reduce levels of CO and other harmful pollutants around us. But during cold starts we have a false impression of cleaner air, given that CO is odorless, color less, in a cold weather, during cold start, catalytic convertors are ineffective, leading to even dangerous levels of exposure such as even more than hundred ppm of CO possible. It takes minimum of five minutes for a catalytic convertor to get warmed up to be effective. Also, in heavy bumper-to-bumper traffic, the air intake directly pulls from exhausts of adjacent cars. The model proposed in this thesis would help educate the commuters of potentially harmful levels of CO. Health conscious commuters could make use of such systems to plan for cleaner alternative routes, pick different commute times of the day, use public transports, use increased car-pooling and thereby reduce levels of traffic congestion during peak hours. This information could also enable city planning, industry set ups and to decide on the location of new industries, regulate policies and aid in the decision to locate school and residential communities on new community development plans.

Current ambient air pollution measurement involves measurement of a specific air pollutant present in the immediate environment. EPA has a specific reference method for measuring each air pollutant. For example, Carbon Monoxide (CO) requires a continuous non-dispersive infrared sensor (NDIR), which is a spectroscopic device used to detect CO level by the absorption of a specific wavelength in the infrared (IR) light. NO/NO2 are measured using the rate of chemiluminescence reaction with ozone. Ozone is measured using the rate of chemiluminescence reaction with ethylene. Particulate Matter (PM2.5 and PM10) is measured using gravimetric filtration sampling. Such devices are expensive and best used under laboratory settings. Moreover, a detailed manual or automatic sample collection, sample analysis, data recording, data analysis, data modeling and pollution forecasting techniques are needed to generate warning and alert messages for excessive levels of air pollutants in the air. Such complex devices and analytical models are out of reach for a common commuter on the road. This creates the need for a low-cost, convenient air quality monitor that common commuters in their car, can easily use to collect and share pollution data.

Electro chemical gas sensors offer an alternative solution to measure and detect harmful gases in the atmosphere at a fraction of cost. Electrochemical sensors operate by reacting with a specific gas by producing an electrical signal, which is proportional to the gas concentration. An electrochemical sensor usually consists of a sensing electrode and a counter electrode separated by a thin layer of electrolyte. The specific air pollutant gas passes through a small capillary opening and diffuses through a hydrophobic barrier so that a proper amount of gas is allowed to react with sensing electrode to produce required electric signal by either oxidation or reduction reaction with electrode materials developed for a specific gas. Electrochemical sensors can be used to measure Carbon Monoxide (CO), Nitrogen oxides (NO/NO2), Ozone (O3) and Sulphur dioxide (SO2). Electrochemical sensors are ideally suitable for real-time air pollution monitoring because of their portability and low power consumption.

There is a multitude of single gas or multi-gas monitors, which employ electrochemical sensors, available on the consumer market for personal use. With an ease of operation of on or off switches, these gas monitors display air pollutant levels on LCD displays. They consume less power and could last up to two years of operation and cost just a few hundred US dollars. One viable option is for commuters to buy these gas monitors and keep them inside the cars. These monitors could alert the commuters immediately on being exposed to higher concentrations of toxic air pollutants like Carbon Monoxide. There is currently no reliable way to share and alert other commuters who might plan on using the same congested streets at the same time. We need a solution where few commuters with personal air monitors in their cars could share the air pollution data with fellow commuters.

With the widespread use of smartphones, there is a huge potential of collecting and sharing air pollution data among interested users. These smartphones nowadays, come with wide array of embedded sensors such as GPS, accelerator, digital compass, microphone and gyroscope. These smartphones also have the ability to communicate with external devices with low power Bluetooth technology, which enable a wide array of sensing applications in the domains of environmental awareness, health, transportation and education. The low-cost, portable gas sensors, combined with connectivity of smart phones provides an ideal solution to build a mobile pollution sensing model that can be easily utilized to build a social community of commuters that collect and share air quality data.

1.3 Online Social Communities for Real-time Air Quality Monitoring

We propose to build a social community of users, who share a common interest of raising air quality awareness that can employ our mobile pollution sensing to gather and share air quality data. In this section, we discuss the advantages of building an online social community. Online social communities are held together by a common interest. The common bond that glues an online social community together may be a goal, social cause, lifestyle, location or profession. The members join an online community to contribute to the common cause or to benefit from the group by being a member of the community. Online social communities differ from social networking sites like Facebook or LinkedIn because people join social networking sites to maintain existing relationships and establish new ones. Usually on social networking sites, people connect with friends, families and with whom they are acquainted, whereas the members of a social community may not be related, but held together by a common cause.

A unique combination of mobile phones, personal air pollution sensors and online social community frameworks offer a perfect opportunity to design a mobile-based online social community of people who are interested in monitoring air pollution levels and sharing the air pollution information to other interested members of the community to help them avoid dangerous air pollution levels. Crowdsourcing air pollution monitoring to a large set of people connected by a environmentally conscious group of individuals, not only reduces the cost, it increases coverage and enables dissemination of timely, real-time air monitoring feed to a wide array of people who might benefit from it. A combination of mobile phones, Bluetooth enabled personal air quality monitors, online communities, crowdsourcing, spatial databases, scalable cloud services and individuals who are passionate about the air quality presents a solution that can be used to provide live air monitor data to millions.

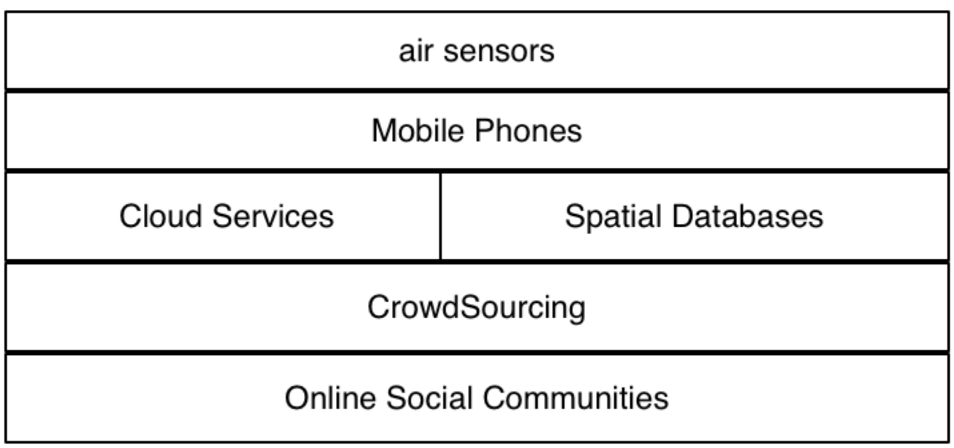


Figure 1-0-2 Online Social Community for Air Pollution Monitoring

There are a wide variety of challenges in establishing an online social community for real-time air pollution monitoring and sharing of information. There are a multitude of different types of personal air pollution monitors that are designed for certain gases such as carbon monoxide or carbon dioxide. Wide arrays of mobile phones are available from different vendors like Apple (iPhone), Google (Android), Microsoft (Windows Mobile) etc. Choosing the right air quality monitor that interfaces with every user's smart phone is a difficult decision. Even harder problem is enticing motivated individuals to participate in a community by convincing them about the validity of the data collected and the benefits of the model. A vast amount of sensor data needs to be managed, filtered and disseminated to millions of users in real-time. Any new design of air quality monitoring systems should consider the data measured for the purpose of evaluating the air pollution effects on people's health. We need to capture relevant information in accessing human exposure to pollutants in terms of time scales, geographical locations, local weather conditions and traffic levels. Moreover, such monitoring programs need to be cost-effective with sufficient community resources to sustain it. Standardization and harmonization of sensor data quality and reference models are important in exchanging and interpreting results. Raw data measured needs to be transformed into useful information targeting the needs of all members of the online social community. Disseminating air quality information helps the public to educate and raise awareness about the health issues related to air pollution.

1.4 Challenges in Building a Mobile Air Pollution Sensing Social Community

We need an accurate air pollution sensor that is lightweight, simple to carry, able to monitor a wide assortment of air pollutants (CO, NO2, and SO2) inside motor vehicles. It ought to be sensitive enough and ready to rapidly distinguish concentration of levels of air pollutants such as Carbon Monoxide within the briefest time conceivable. Sensor module, likewise, needs to record barometrical readings like temperature, pressure, humidity and so on. The sensor module needs to be sturdy and equipped with batteries that can be easily charged using the car charger. It needs to have either Bluetooth or wireless communication that is more energy efficient and able to communicate live monitor readings to a remote device such a laptop or smart phone. The device needs to have a GPS device or Smartphone should be equipped with GPS mechanism to identify geo location co-ordinates. The device or smart phone needs to record these readings with timestamp and able to cache data for a duration when the Internet connectivity is not available. When Internet connectivity is available it needs to sync up data as soon as possible to a backend service and clean up any cached information. The sync up needs to happen as quickly as possible so that live monitored data is available to the other community members. We also need to process any outliers in data readings and purge those outliers. The backend database should have be able to support any spatial queries like "what are readings within two miles of my current GPS location (latitude, longitude)". The backend service should be scalable horizontally as the demand for data and monitor recordings increase. The data exchange format should be standardized and able to work on heterogeneous operating system environments. For consumers of air monitoring data, it needs to be easy to use and able to display accurate air quality with current location on map display with streets. The online community needs to support registration of members, registration of monitoring devices, enable account/profile management and ranking within community based on the contribution levels.

1.5 Thesis

The purpose of this thesis is to research, analyze existing air quality monitoring techniques and controls and build a mobile sensing model and framework to facilitate real time monitoring of air quality and disseminate the information to citizens interested in consuming air quality data. The key focus is to model an online social community of users who are motivated to collect and share air quality data using their mobile phones and portable air pollutant sensor devices. The online social community for air pollution sensing would support features like user registration, sensor registration, regional subscription for real time air quality data feeds and real time map representing pollution data.

There is a lot of research and attempts made to build a portable model of air quality sensors. These efforts mainly focused on design of wearable sensors that would be used to collect data along with geo location coordinates and process the data using a backend server and provide air quality index information to the users. Because the approach involved laboratory built electronic circuit boards with electro-chemical sensors and custom back end servers, they lack real time usability, flexibility and ability to provide real-time data feeds. They are also usually designed to be mounted external to the motor vehicles and are very difficult to use for an ordinary citizen. In this thesis, we present a more efficient approach using easy to own low power gas sensors combined with existing smart phone technology that connects to scalable cloud based data services. The sensor model includes out of shelf electro-chemical sensor, microcontroller and Bluetooth transmitter to connect to the smart phone to publish air sensor data. Our model makes use of existing smartphone capabilities for efficient data storing and replication to the remote cloud servers. Users are able to not only collect but also share such valuable real time pollution data with fellow community members. Commuters will be able to get instant valuable air quality information about their environment. We expect it would gradually change perceptions about air pollution and would help to formulate better air quality control policies.

Our thesis involves creation of an easy to use iPhone application that can be used to view current street level air pollution levels of the current user location. If the user is having a personal air pollutant monitor, it can be registered and used to collect and share the air pollution data with other community members. Mobile air pollution monitoring can be used to augment the existing stationary air monitoring systems. Mobile air sensors can be used to improve the overall accuracy of the air pollution measurement where current data is not available. A good example is highly congested roadways during peak travel times. It will be used to measure the air pollution within the closed environment inside motor vehicles. Since the costs of electro-chemical gas sensors and smart phones are less prohibitive and since computational and power consumption levels are low, we can easily realize a practical adaption of such mobile air quality sensing online community.

1.6 Related Work

Due to the huge gaps in ground-based static networks of air pollution monitors, there is a necessity to obtain fine-grained air quality data. Various attempts have been made to employ mobile sensors in order to achieve this goal. The School Bus Monitoring Study [25] conducted at University of California along with NRDC (National Resources Defense Council) highlights the health hazards posed to school children by their exposure to diesel pollutants. It also emphasizes the urgent need for mobile monitoring of air quality because diesel exhaust is a known carcinogen and a cause of respiratory illnesses. An interesting study was conducted by EPA [18] to measure air pollutant concentrations inside and outside truck cabs. The study however used measurement techniques that involved collecting air samples in the truck and later analyzing them in a lab to derive actual air quality values. The setup used in these studies were conducted on stationary trucks for a fixed period of time. Our thesis proposes a model that overcomes the challenge of collecting gas samples in bags and later analyzing for pollutant levels by the use of electrochemical gas sensors. Wireless sensor networks for monitoring personal pollutant exposure [19], indoor air quality [17] and hazardous sites [24] have also been proposed.

In order to bridge the gap between the sampling phase and the analysis phase, researchers introduced monitoring approaches using commodity sensors, which can provide real time pollution data. N-smarts [20] and CommonSense research conducted jointly by UC Berkeley and Intel focused on collecting air quality data by attaching sensors to GPS enabled cell phones. It also highlights various challenges with the quality of sensor data from networked mobile sensing units such as interference of user behavior, location coverage, calibration accuracy and social aspects of mobile sensing and impact on citizen behavior. A custom model was built for the purpose of this study. Such models are not readily available for users interested in monitoring air quality data. Hence our work focuses on using commercially available off-the-shelf air quality sensors that will ensure better adoption and use of our proposed model.

Work has also been done to evaluate the design issues of sensor boards for air quality monitoring [16]. The challenges in preserving privacy of participants of personal sensing have been studied [22, 23]. A software framework for data gathering using smart phones has been presented in [21]. Air Quality Egg [27], a project hosted on Xively (formerly Pachube/COSM) has introduced a personal pollution-sensing platform. The Air Quality Egg can be installed at certain locations near homes to monitor stationary air pollutant levels. Our work proposes a model that is mobile and can be used in cars to provide real time air quality data at all the locations travelled by users.

OpenSense [12], a project run by EPFL and ETH Zurich, Switzerland, aims to study the feasibility of installing sensors on the roofs of buses and trams, taking advantage of existing public transportation vehicles to form an extensive network of mobile air quality data collection sites. Similar pollution sensing network has been tested on the buses in the city of Sharjah, UAE [14]. Our thesis aims to bring similar air quality monitoring capability to the hands of all commuters in their personal vehicles, which can help to provide very fine grained air quality information to users. The Air Project [13] is a public, social experiment in which people are invited to use portable air monitoring devices to explore their neighborhoods and urban environments for pollution and fossil fuel burning hotspots. Teco Envboard [15] focused on design of sensing platform with commercial off the shelf sensors for carbon monoxide, carbon dioxide, ozone and nitrous oxide for urban/participatory sensing projects. Another interesting approach discussed in [26], wherein; the historical and real-time air quality measurements are used to infer the fine-grained air quality in a city. Similar learning techniques could be applied to the data collected by our mobile pollution sensing model to predict dispersion of pollutants and air quality in areas where active monitors are not available.

1.7 Summary of Thesis Contributions

This thesis makes the following contributions:

- It describes the design of a Mobile Air Pollution sensing Social Community model that leverages smart phones to collect and share pollution data. Using a portable air pollutant sensor device with Bluetooth connectivity that interfaces with a custom iOS application, our model enables collection of air pollutant level data by users in vehicles and sharing it with fellow community users in real time. This also alerts users to avoid areas of dangerous pollution levels.

- Through a prototype, it compares the fine-grained data collected using Mobile Air Pollution sensing model with available data in current stationary air pollution monitoring stations. It demonstrates that combined with available data about air quality, data collected using our system demonstrates the spatial granularity of the air pollution around us.

The mobile pollution sensing model was published in

Real-time Air Quality Monitoring Through Mobile Sensing in Metropolitan Areas. *In Proceeding of the 2nd ACM SIGKDD International Workshop on Urban Computing (UrbComp'13), August, 2013.*

1.8 Contributors to the Dissertation:

This section lists the co-authors of the papers from which the materials are used in this dissertation and the contributors to this thesis. The mobile pollution sensing application and backend prototype was built in collaboration with my advisors Prof. Liviu Iftode and Prof. Badri Nath. The calibration of Node devices in Chapter 5 was under the guidance of Prof. Ann Marie and experiments conducted in collaboration with Avraham Teitz at United States Environmental Protection Agency, Edison, NJ. Mansi Parikh contributed to the method detection limit for Node devices, presented in Appendix E.

Chapter 2

Mobile Air Pollution Sensing Community

This chapter describes the design of the mobile air pollution sensing community. In the first section, it defines the design goals for a mobile-based air pollution sensor subsystem, and subsequently, discusses the associated challenges and strategies. This is followed by a detailed description of the various components of the system.

2.1 Design Goals

For realizing a mobile-based air pollution on-line social community, we need to have a very lightweight, self-powered sensor module that could detect air pollutants like CO/NO2/SO2 with high precision. Sensor module needs to be easy to carry, function continuously and able to maintain battery charge for at least a day. The various feeds from different sensor devices need to be shared with fellow community members. In order to have an effective air monitoring system, the pollution sensing community must achieve the following goals:

1. The sensor module at minimum, shall detect air pollutants like Carbon Monoxide (CO) with high precision and able to function continuously.
2. The system must interface with mobile smart phones especially iPhone and transfer sensor readings.
3. The mobile application module must be able to collect these sensor readings, time stamp them, geo tag them and cache them temporarily until optimum Internet connectivity is available and then sync with remote servers.
4. The mobile application module must be able to display street level maps and pollution levels of various pollutants based on user's current geo location.
5. Community members must be able to register, maintain account profiles, and register sensors modules and share/consume readings.

2.2 Design Overview

The design of a mobile-based air pollution on-line community is based on the following observations:

- Most commuters spend a considerable amount of their time inside the car while travelling and breathe air circulating inside the car.
- The pollution levels outside on the roads we travel have a direct impact on the air quality inside the car
- Air pollution levels on highways and roads are dynamic and vary depending on the time of the day, traffic levels, atmospheric conditions like wind speed, temperature, humidity etc.
- Latest developments in electro-chemical gas sensors provides highly sensitive, in-expensive portable sensors
- Majority of us carry a smart phone with GPS, Bluetooth and Internet connectivity.
- Cloud infrastructures like Amazon EC2 provide scalable remote server architecture for managing increased demands of client requests and data.
- Maturity of spatial databases like PostgreSQL with spatial extensions like PostGIS enable us to simplify geo location based queries.

Our design intends to synthesize electro-chemical sensors, smart phones, cloud services and spatial databases to enable an air pollution information sharing community of interested users. Significant portion of the research was involved in choosing an electro-chemical sensor module, building iPhone application, spatial-query enabled web services and analysis of results. Many gases such as H2, O2, CO, NO2, NO, O3, SO2 and H2S can be measured with specifically designed electrochemical gas sensors. Appropriate materials for sensor, sensor geometry and dimensions are critical for optimum performance of gas sensors. Electro chemical properties of the sensor materials, geometry and physical dimensions of the sensor device have direct correlation to the response time, accuracy, durability, precision, electrical signal quality and sensitivity of the sensor device to the gas under study. For example, in a typical CO gas sensor, the molecules of CO are oxidized at the anode surface to produce CO2 [33]. The current generated on the sensing electrode is related to the rate of CO reaction.

$CO + H_2O \Rightarrow CO_2 + 2\,H^+ + 2\,e^-$

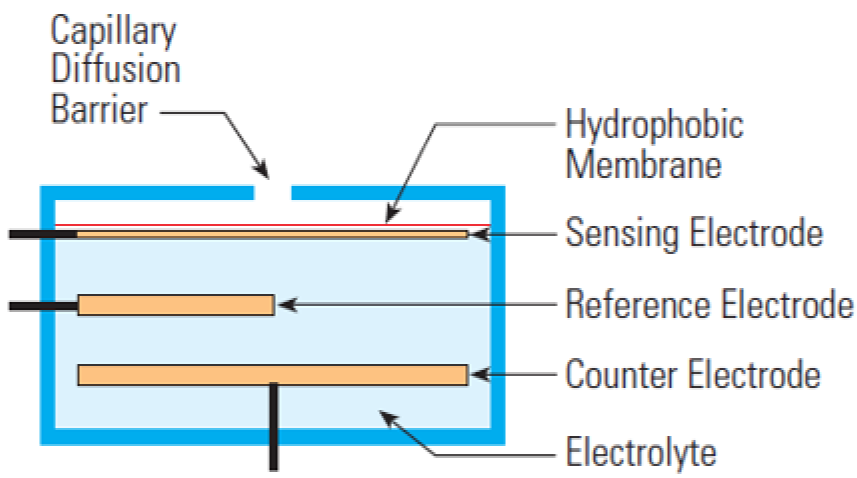


Figure 2-0-1 Three Electrodes Electrochemical Sensor. Adapted from "Hazardous Gas Monitors: A Practical Guide to Selection, Operation, and Applications", by Jack Chou, 1999.

A typical electrochemical gas sensor consists of a filter, membrane, sensing electrode, electrolyte, counter electrode and reference electrode. Faraday's law can be applied to relate the observed current i.e. sensor signal to the number of reacting gas molecules which directly relates to the gas concentration levels.

$I = nFQC$

Where I is the current (C/s), Q is the rate of gas consumption (m^3/s), F is the Faraday Constant (9.648×10^4 C/mol), C is the concentration of the analyte and n is the number of electrons per molecule participating in the gas reaction.

Electro-chemical gas sensors market is well developed now and sensors for electro-active gases like CO, NO, NO2, O3, H2S, SO2 are easily available. Typically such gas sensors output current. Most of the micro controllers operate with voltages. We need an Analog Front End (AFE) to amplify current levels, filter out high/low frequency noise and convert current into voltage levels suitable for a micro controller. Usually, microcontrollers come with analog-to-digital convertor circuitry for translating sensor signals into a digital format. Bluetooth transreceiver attached to the sensor enables interfacing with the iPhone.

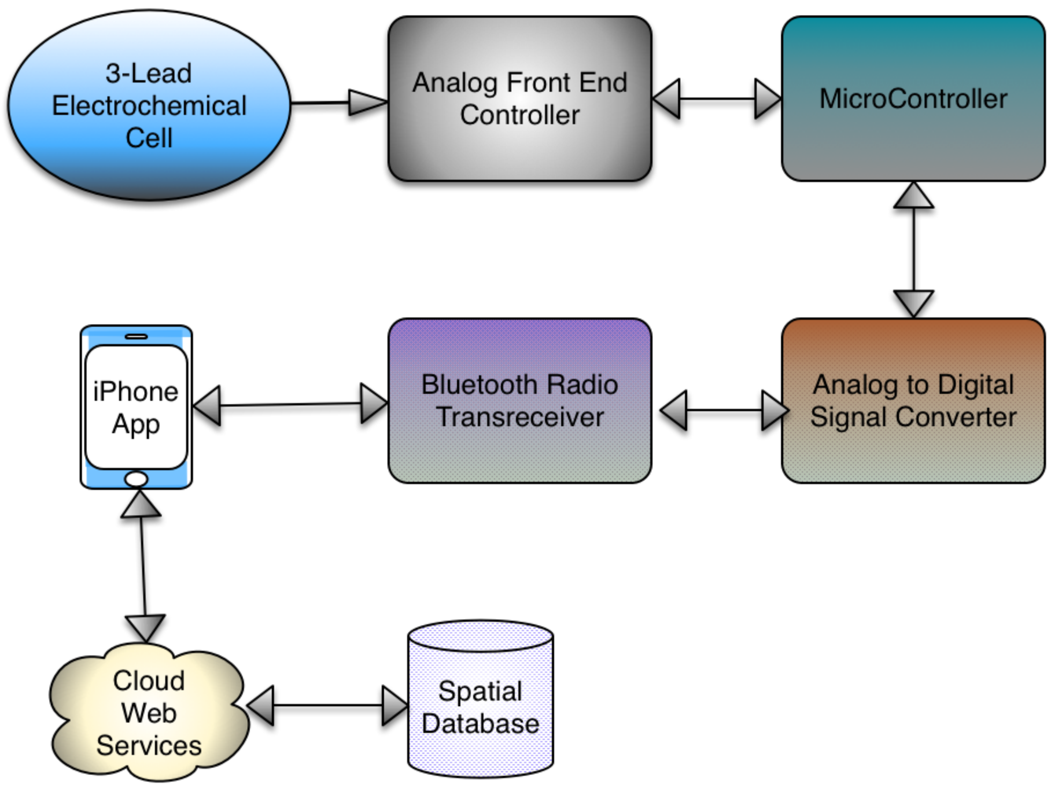


Figure 2-0-2 Sensor Architecture Diagram

There are two options in designing personal sensing device. As part of this project (previous work as part of the same project), a custom mobile sensing prototype was built consisting of a microcontroller, gas sensors, GPS and a cellular modem which can be mounted on public transportation vehicle and can be powered by the vehicle's battery. In the prototype design, we used the Arduino Mega128 microcontroller, SIM5218 cellular modem and PMP 648 GPS receiver. MQ-7 Carbon sensor from Hanwei Electronics was used as gas sensor. The cost of assembling such unit was around seven hundred dollars and it required a twenty five dollars per month cellular data plan. Such a custom sensing model is more suited for installing on public transport vehicles due its size and power requirements. Hence a different sensing model was needed for everyday commuters to carry conveniently in their personal vehicles. The alternative approach is to come up with a personal sensing device using an out of shelf product. In this design, we have used a NODE wireless sensor platform available for smart devices from Variable Technologies [11] that include an electro-chemical sensor with pre-assembled Analog Front End, LMP91000 from Texas Instruments and CC2541 as Bluetooth transreceiver. The device is shown in Figure 2-0-3. The NODE sensor platform is customizable with add-on sensor modules. Each device can accommodate two sensors on either end of the device. We selected OXA and CLIMA modules to measure carbon monoxide, humidity, temperature, ambient light and barometric pressure. Our main criteria for choosing this sensor platform were its size and easy to use design. NODE uses Bluetooth connectivity to interface with users' iPhone device to transmit the pollution levels in the environment. The NODE device along with the OXA and CLIMA sensor modules costs about $300. In addition, user's existing iPhone device and data plan or Wi-Fi can be used to transmit data periodically to the server.

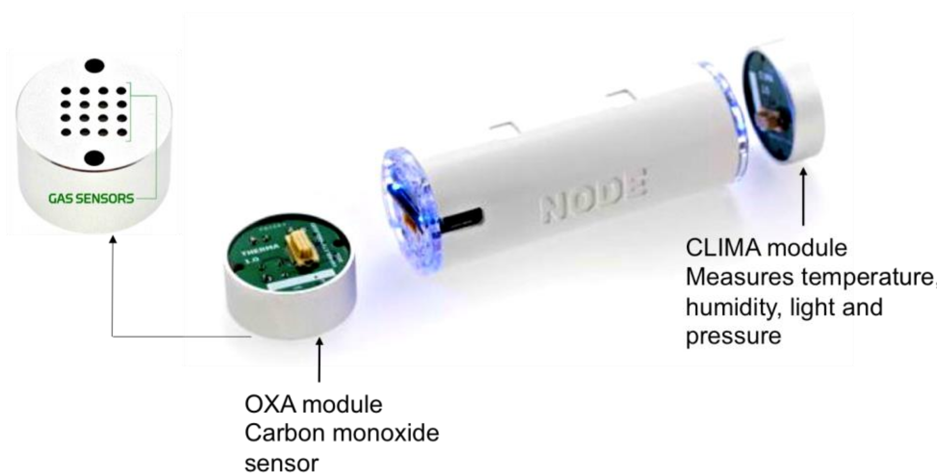


Figure 2-0-3 Variable Technologies NODE Sensor Platform

NODE sensor platform also comes with in-built rechargeable battery which once charged can be used for twelve hours. This is very important for continuous streaming of sensor data to the iPhone, if required and the battery charge lasts up to fifty four days in standby mode. So, it is very convenient to carry around. With USB compatible car charger, it can then be used continuously while driving. Moreover, it is 2.75 inches in length and 1 inch in diameter, weighs about 38 g and with a range of 100 m for Bluetooth connectivity, it is highly convenient for mobile sensing purposes. It has an OXA sensor attachment, which can be attached to either end of the device. There are various OXA sensors available for each type of gas such as CO/NO2/H2S/SO2. For example, the OXA CO sensor can measure CO from 0-400 ppm (parts per million) with resolution of 1.5 ppm and it can operate with a temperature range from -20 C to 50 C that makes it ideal for commuters for day-to-day use.

2.3 Mobile Application Design

As part of this thesis, a custom iOS application, weBreathe, was developed to build the social community of mobile pollution sensing users.

Primary goals of the app:

- Able to interface with Node sensor platform over Bluetooth
- Able to interface with iPhone's location services to collect GPS co-ordinates (longitude and latitude)
- Able to display street level map with pollution level overlay in two hour intervals to show pollution trends
- Able to cache sensor data on the iPhone storage, until optimum Internet connectivity is available.
- Provide users with option of using cellular data or only WIFI to connect to cloud services for transmitting data
- Provide option for consumers that do not have sensor devices but want to view pollution data
- Provide option to participate in the online social community
- Display community member rank status based on the participation level.

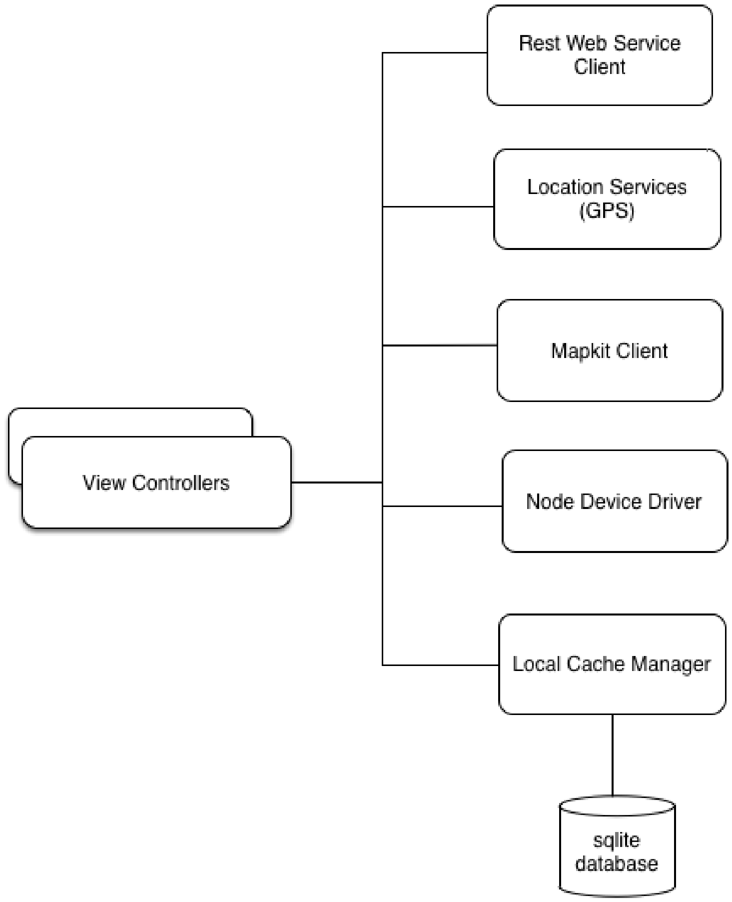


Figure 2-0-4 weBreathe iPhone Application Architecture

weBreathe application architecture consists of a set of view controllers whose main purpose is to manage screen flow and UI element interactions. View Controllers interact with a custom Restful Web Service client component, which manages all of the data exchanges, and error handling with remote cloud based web services. Location services delegate component interfaces with iOS location services to get current user location co-ordinates. The Map Kit client component closely works with view controllers, restful web service client and view controllers to display current street map with pollution level overlays. The node device driver interacts with Bluetooth layer to communicate with the Node sensor module to collect air pollutant concentration levels. Local cache manager makes use of SQLite database to temporarily cache sensor readings until they are synchronized with the remote web services.

2.4 Social Community Design

Social media refers to interaction among people in which they create, share and/or exchange information and ideas in virtual communities and networks [34]. Social media can be functionally classified as

1) Social networks

2) Social community

Social networks: the members of a social network are connected to other members by the interpersonal relationships they share with them. The primary focus in a social network is the people that form the network.

Social community - Social community is a group of people that connect for a common cause. The common interest is what holds its members together. The members of a social community may be from all walks of life and have no relationship amongst each other [35].

We propose to build such a social community with the common goal of getting firsthand information about the air pollution around them and sharing it with others in the community. Studies about online social communities indicate that the key to building a successful e-community relies on user experiences and perceptions about the group that want to join. People need to believe that they get some value by joining an e-community. There should be a positive return of investment for the time and energy an individual contributes to the online community. Our design of air pollution online community model is based on the following principles [47].

a. Perceived Benefit - We want to motivate the individuals to join the online-community because there is clear advantage of obtaining real time information about the air pollution around them and this information is easily accessible from a simple touch on their iPhone. Our design also focuses on individuals who have strong desire to improve the air quality and do not mind investing a few hundred dollars on a Node sensor device and contribute to sharing air pollution information with others. We also focused on creating an intuitive and easy to use application with clean user-friendly user interface.

b. Group Cohesion - Our design focuses on building a group cohesion based on location based air pollution data. The contributors who own the sensors have substantial influence in contributing to real time data. We designed a ranking system, which adds points based on the amount of the air pollution data shared with others. We want to influence the feeling of belonging to the community by establishing a shared goal of creating a cleaner environment for us and for the future generations. The membership to the group is made simple with a simple user registration with minimal personal profile data collection.

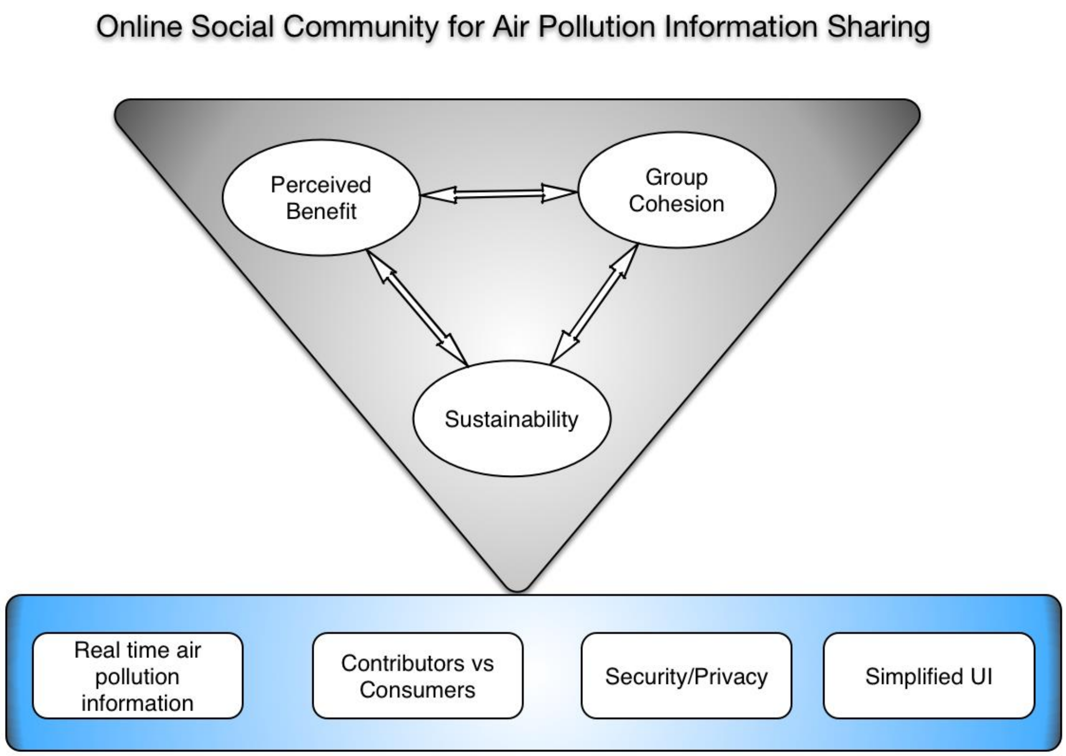


Figure 2-0-5 Online Social Community Design

c. Sustainability - The sustainability of an online community depends on fostering broad citizen participation in the implementation. We want to build a community, which is inclusive of diverse members like consumers and producers of air pollution information. We want to build an open source client application and server components that can be hosted and supported by various community members and further developed to support various sensor devices. We also focused on protecting privacy of user locations and restricting sharing of user profiles. Our design focuses on members taking full ownership and responsibility of air pollution data they share.

2.5 Cloud Services Design

For the backend to our application, we needed a reliable server infrastructure to store, process and push data to clients. We explored various options available for this purpose. Setting up our own hosting server was one of the options, but it involves infrastructure and maintenance costs. This was also not a very scalable option. Also a dedicated administrator would be required to monitor and maintain the physical server.

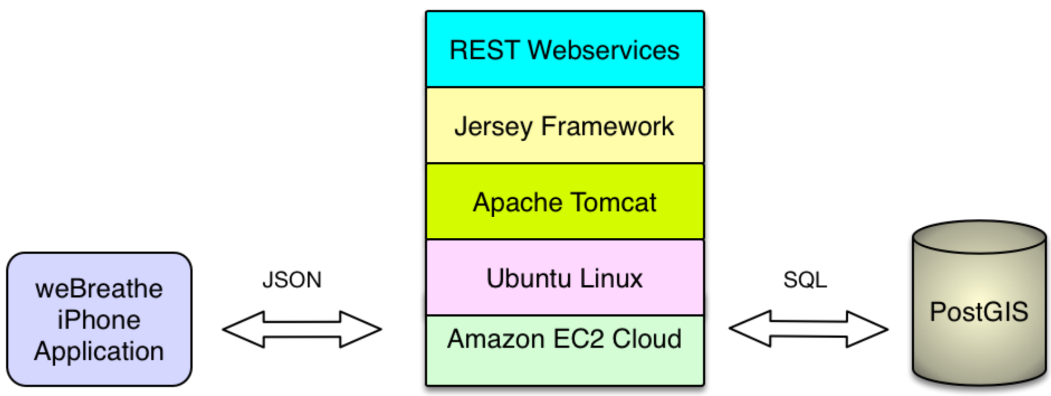


Figure 2-0-6 Cloud Services Architecture

We would need to address connectivity, security and scalability in our infrastructure. Another option was to use the readily available cloud infrastructure. Cloud web services provide reliable, scalable infrastructure needed to deploy web solutions with least administration costs. We want to design our remote web services to provide resizable compute capacity in the cloud so that multiple virtualized instances can be provisioned to scale up or down capacity as the community usage grows/shrinks. We have chosen Amazon Elastic Compute Cloud (EC2) to provide cloud-hosting services. Amazon EC2 allows using web service interfaces to manage virtual operating system instances, configure network security permissions and run multiple instances depending upon the client request loads. We have adopted Representational State Transfer (REST) Web services as they provide an easier-to-use, resource-oriented model to expose backend data services for sharing air pollution data. Our implementation follows four basic design principles

- Use of HTTP methods (GET/POST/PUT/DELETE) to establish one-to-one mapping between create, read, update and delete operations.
- Increase scalability by being stateless because stateless server-side components are less complicated to design, write and distribute across load-balanced servers.
- Simplified resource representations using directory structure-like URIs
- Use JavaScript Object Notation (JSON) to transfer data as this reduces parsing overhead and data mapping between data transfer objects

In order to simplify development of RESTful Web Services, we have used Java based Jersey Web Services open source framework deployed on an open source Java Servlet container, Apache tomcat. For storing sensor readings along with geographic location co-ordinates, we have used PostGIS that is a spatial database extender for PostgreSQL object-relational database. PostGIS adds support for geographic objects allowing location based SQL queries. The PostGIS implementation makes use of lightweight geometries and indices, which are optimized to reduce disk and memory usages, thereby improving query performance.

2.6 Pollution Sensing Inside Motor Vehicles

According to the report by the International Center for Technology Assessment (CTA), levels of some air pollutants such as carbon monoxide (CO) are up to ten times higher inside vehicles than at fixed monitoring stations [28]. The variations depended on the pollutant, the type of road, the level of traffic and the type of vehicle being followed. Surprisingly, the study also finds, due to the vehicle ventilation systems, the Particulate Particle (PM) pollution levels are 20-40% lower inside the cars.

A highly polluting vehicle such as a heavy-duty diesel truck that is directly in front of a motorist accounts for 50% pollution inside the car. Pollution inside the car was worse during freeway rush hours and also while the car is driven in slow moving right lanes.

For the individual commuter, monitoring using a personal NODE device would facilitate identifying dangerous pollution levels inside the car and take precautionary measures like rolling down the windows during lesser traffic to increase air circulation.

Figure 2-0-7 Node Sensor Setup Inside Car

Studies conducted by EPA in the 1970s [29] shows that the pollutants in motor vehicles find their way into their interiors. On many occasions, the pollutant levels inside cars are more than those outside the vehicle. The pollution levels inside the cars are higher when traveling on heavily congested roads or passing through busy intersections or while following diesel trucks or buses and older cars. It is clear from the studies that pollution levels inside the cars are due to the exhaust from other vehicles in the immediate vicinity. Based on a 1998 California Air Resources Boards study [30], it is clear that especially very fine particle matter (PM) levels are higher inside car than that of outside. Even though car's ventilation and air conditioning systems filter out larger particles, passengers inside the car usually exposed very dangerous fine particles. As per studies by the researchers from the Department of Environmental Health, Harvard School of Public Health [31], the average in-car CO level is nearly 97% of the car exterior CO level average and was 3.9 times the average for the ambient air CO level recorded by the remote CO monitoring sites. In the studies CO levels inside the car ranged from 1 to 32 ppm, with an average of 11.3 ppm. CO levels immediately exterior to the car range from 6 to 22 ppm with an average of 11.7 ppm. But the CO readings from nearby fixed monitoring sites showed a range from 1.7 to 5.5 ppm with an average of 2.9 ppm.

As per the model proposed by Flachsbart and Ah Yo (1989) [32] on commuter exposure to CO, the total mass of CO within the vehicle interior is equal to the balance of the CO entered, exited, emitted and reacted within the area volume inside the vehicle. The model predicts commuter exposure to CO inside a car by exponentially diffusing CO concentrations just outside the car and by exponentially decaying initial CO concentration that was already inside the car.

Average CO Exposure of the commuter = Observed CO Concentration on the roadway

+ (difference between CO concentration already present within the

vehicle and Observed CO Levels immediately outside the vehicle)

$* (1-e^{tr/T}) * (T/tr)$

Where e = 2.71828 and T is the time constant in seconds and tr is the time the vehicle spends within the roadway. The roadway CO concentration is dependent on traffic speeds, ambient temperature, and types of vehicles present on the road, vehicle speed and number of vehicles present on the road. Even though the actual commuter exposure to CO and other air pollutants is very dynamic and varies depending on roadway CO concentration, our thesis focus is to share and communicate a typical commuter exposure to CO concentrations to fellow commuters who would be travelling under the same roadways and under nearly identical traffic situations.

2.7 Spatial Query Design

Spatial data is one that describes either a location or shape, for example, roads, house location, rivers, municipalities, and lakes. Spatial data, in simpler terms, is represented as points, lines and polygons. For example, roads can be represented as lines. Spatial data can be used to model relationships between spatial objects like proximity, adjacency and containment. In conjunction with other data, spatial data allows to model a complex spatial relationship. Spatial databases like

PostgreSQL with PostGIS extension allow us to treat spatial information as any other database object. PostGIS allows us to use simple SQL expressions to determine spatial relationships like distance, containment and perform spatial operations like intersection, area and union.

In our thesis, all of the sensor readings are collected along with longitude and latitude co-ordinates from iPhone location services. The GPS co-ordinates are stored as a spatial data type of point.

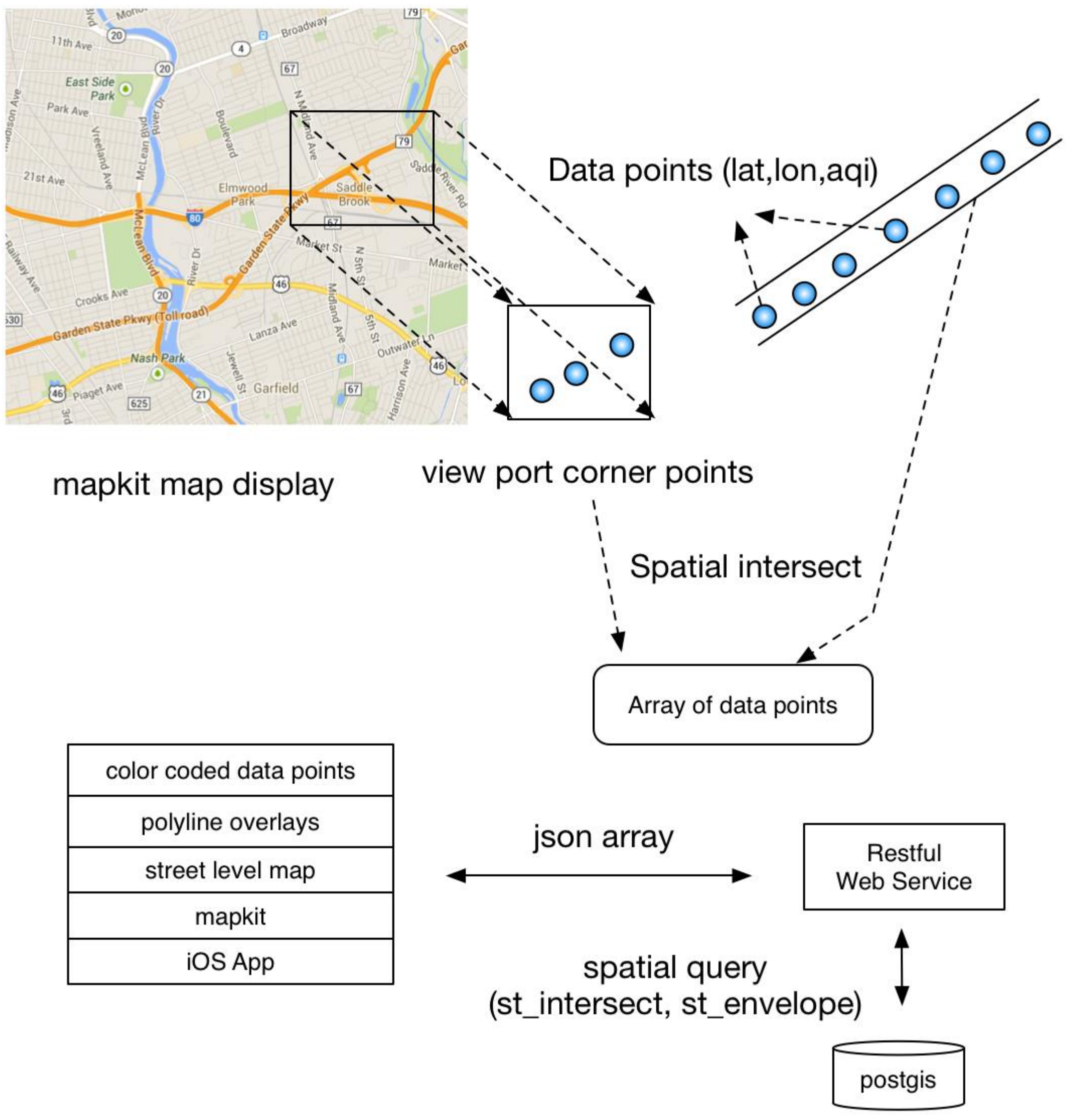


Figure 2-0-8 Spatial Design

In our model, the pollution data is collected when the user uses a sensor inside the car and travelling along the roadways. With the optimum time interval between successive sensor readings, the GPS co-ordinates would closely map the shape of the roadways. The pollution information in our design is conveyed to the user on a roadway map using Apple's MapKit interface. The pollution data points are drawn over the map as polyline overlays. Because the map can be zoomed and navigated around by the user, we use the maximum view port area co-ordinates and perform a spatial intersect query to get all the GPS co-ordinates for which we have pollution data available within a certain time frame (last two/four/six/eight hours) that lie within the rectangle area visible on the map.

Air Quality Index Levels of Health Concern	**Numerical Value**	**Meaning**
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health warnings of emergency conditions. The entire population is more likely to be affected.
Hazardous	301 to 500	Health alert: everyone may experience more serious health effects

Figure 2-0-9 EPA AQI Color coding

We developed a web service which would return a JSON array of pollution data along with GPS co-ordinates given the max/min latitude and longitude values. The web service first creates spatial envelope making use of area to be shown on the map by making use of ST_Envelope function which returns a geometry object representing the bounding box defined by the corner points. It then selects all of the pollution data points which intersects with the bounding box by applying spatial intersects operator. This approach greatly reduces the amount of data exchange and limits the data points to what can be reasonably viewed by the user using the map display. The pollutant concentration levels are color coded as per EPA guidelines, as shown in Figure 2-0-9 [8] for the air quality index calculated from the data points. It makes it easier for people to understand quickly unhealthy air pollution levels they might experience along the roadways they are travelling. For example, color green denotes the air pollution poses little or no risk while red denotes the air pollution levels may be unhealthy for everyone.

Chapter 3

Implementation

This chapter describes the implementation details of the real-time mobile pollution sensing online social community. In the opening section, the hardware components used in the implementation are described. This is followed by the implementation details of the iPhone application. It then describes the various modules used to implement server side components of the online social community.

3.1 Hardware

Our key decision was to choose a commonly available gas sensor device, which is inexpensive, easy to handle and use and one that also provides accurate real-time sensor readings. We have chosen variable tech's Node sensor OXA module as a preferred choice of gas monitoring device.

Very easy to attach OXA modules are available for Carbon Monoxide (CO), Nitric oxide (NO), Nitrogen Oxide (NO2), Chlorine gas (Cl), Sulfur Dioxide (SO2) and Hydrogen Sulfide (H2S)[3]. The other end of the node device can be attached with Clima Module that can measure temperature and humidity. Node device is especially very lightweight, inexpensive, easy to carry and ideal for quick adaptation by the social community members. The node sensor can be used as it is inside the car. For outside of car, we have built a prototype with easy to assemble components along with Node sensor.

3.2 weBreathe iPhone Application

The primary goals of weBreathe iPhone application are ease of use and to provide timely, accurate pollution information along the roadways. The first step in using the application is user

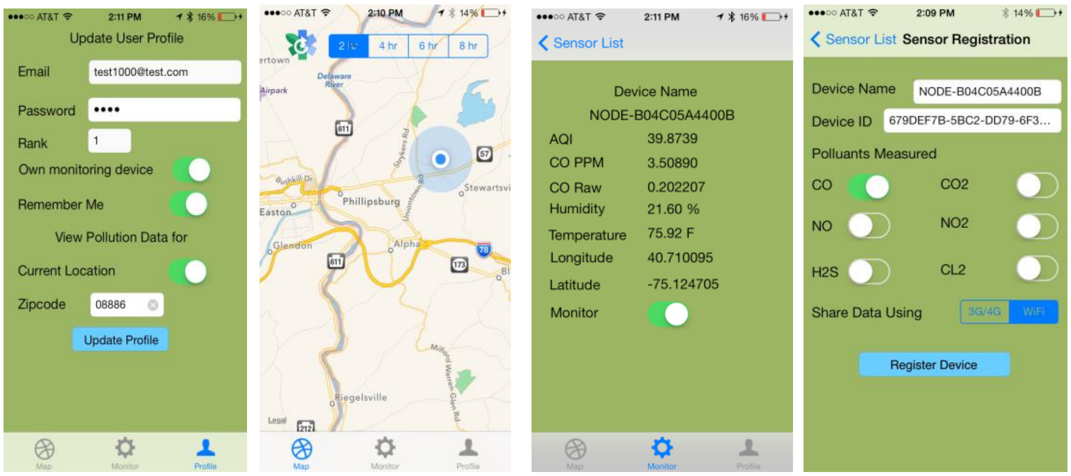


Figure 3-0-1 weBreathe iPhone Application User Interface Screens

registration. The user profile consists of email address, password, node device id, pollutant sensor type (CO/NO/NO2/H2S/CO2/CL2) and user preference to share sensor data using cellular data plan or WIFI connection and option to select if user is interested in viewing pollution data for the current user location or only for a certain zipcode. User sensor device registration is an optional feature available. In the map display, user has an option to display last 8 hours of pollution data with 2 hours intervals. weBreatheNavigationController class manages showing various ViewControllers like LoginViewController, MapViewController and RegistrationViewController. MainTabBarController presents tab bar with three options map, monitor and profile. MonitorViewController class has the responsibility of interfacing with NodeDevice via VTNodeManager Class and transmits pollution readings to the remote web service using RestClient class. Depending upon the data sync option selected by the user and the available Internet connectivity, the sensor readings are temporarily stored in the local SQLite database using the class SensorReadingDAO.

Reachability class monitors change in Internet connectivity. NSTimer class is used to schedule data synchronization activity at a predefined interval. Node device driver is used to interface to the Node device over Bluetooth connectivity. VTCoreLocationController class is responsible for getting GPS location updates.

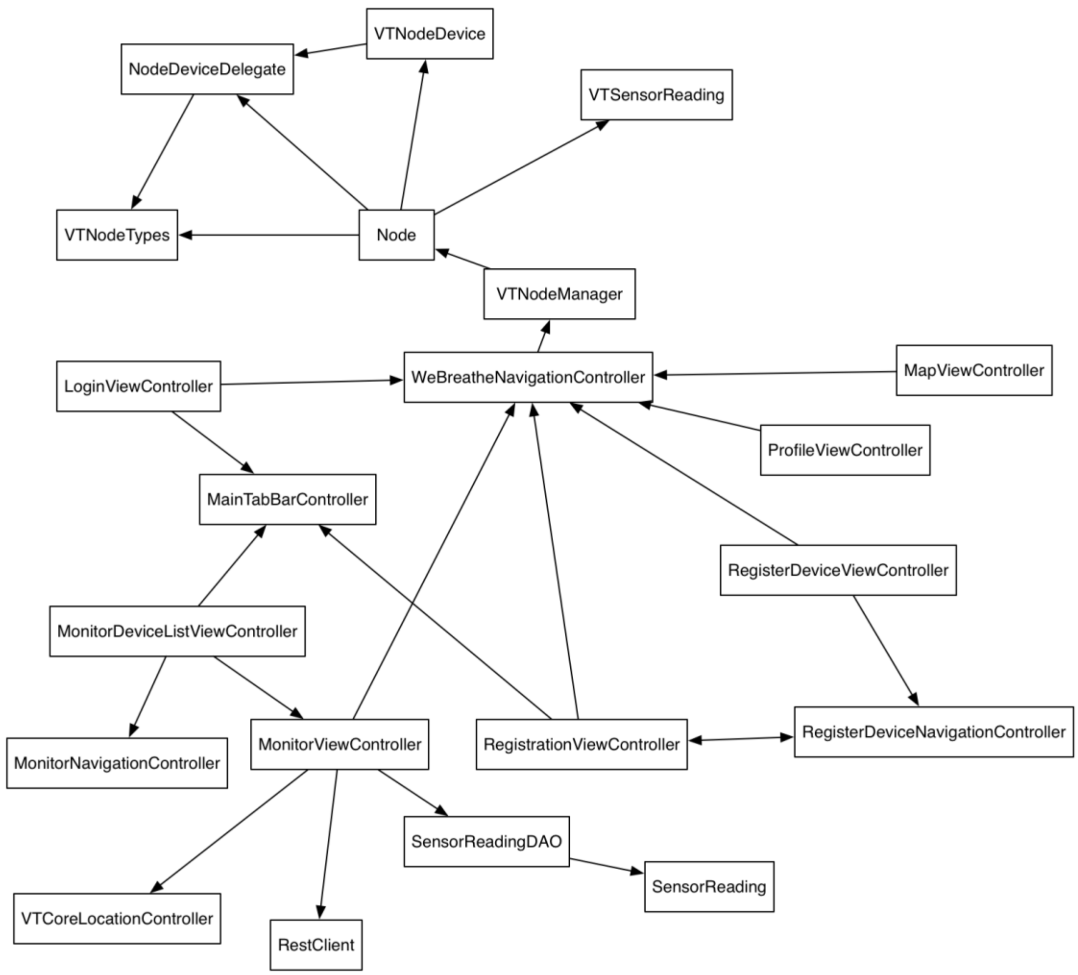


Figure 3-0-2 weBreathe Class Interaction Diagram

RestClient gets map display pollution data in JSON format from the remote web service and interfaces with MapViewController to display map overlays of pollution levels.

3.3 weBreathe Web Services

To record sensor readings, we have developed a RESTful webservice called Sensor_ReadingService, which takes in an array of JSON objects representing node sensor readings. In order to simplify the development of RESTful webservice, we have used Jersey

RESTful Web Services framework. Jersey is an open source framework, which supports developing java web services using JAX-RS apis. A JAX-RS resource is an annotated plain java object that provides resource methods that are able to handle HTTP requests for URI paths that the resource is bound to. In our case, the resource exposes a single resource method that is able to handle HTTP POST requests, is bound to /Sensor_Readings URI path and can process an array of Sensor_Reading objects represented in "application/json" media type.

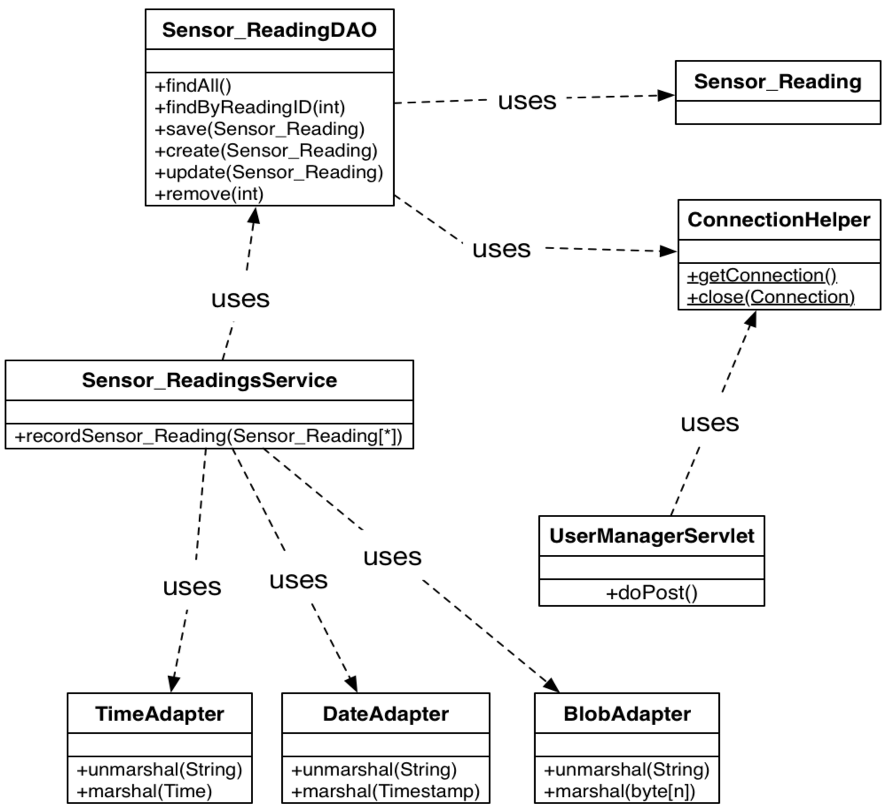


Figure 3-0-3 weBreathe WebServices Class Interaction Diagram

TimeAdapter, DateAdapter and BlobAdapter classes are used to marshal and unmarshal time, date and image objects in the JSON payload. Sensor_ReadingDAO class manages all of the PostgreSQL database queries for saving sensor readings. Sensor_Reading class is the data transfer object (DTO) representing a sensor pollution reading collected. UserManagerServlet supports all of the social community functionalities like user registration, login, update user profile, map view based sensor readings queries etc.

Chapter 4

Optimization

This chapter discusses various optimization techniques implemented in the mobile pollution sensing online social community model. In the initial section, it lays down the goals of the optimization process and explains what we intend to achieve by these optimization techniques. Then, it briefly describes the details of the challenges and the solutions engineered to overcome these challenges. Results of the optimization are then described to save network data usage, smartphone battery power, amount of storage needed to store readings, map display efficiency and timely sharing of pollution data with other online social community members. In the final section, we explore a simple outlier elimination model to filter out temporal spikes in sensor readings.

4.1 Goals

In order to be an effective online social community for sharing pollution data, the model should provide timely, accurate pollution information to its community members. Since the key component in the model is the mobile application, it needs to be easy to use, provide a simpler user interface to display pollution data along the roads. The client application must perform efficiently on the iPhone platform by consuming least possible amount of battery power. There are two larger groups of online social community users, consumers and producers of pollution data. Producers are those members who carry the Node sensor devices inside their car and use the iPhone application to measure the pollution levels as they travel and transmit data to the remote web services. Consumers are those users who just use the iPhone application to know about the pollution levels along the roadways they travel. For producers, the application needs to incur least amount of cost for cellular data transfer. For consumers, the pollution map display should have high performance and responsiveness with least amount of data transfer to reduce network overhead and battery power consumption. Finally, the system should detect any temporary changes in sensor readings and remove outlier values.

Our main goals for optimization can be listed as follows:

- Efficient data transfer.
- Reduced network data transfer cost.
- Highly responsive map display with pollution overlay.
- Reduce energy consumption of iPhone battery.
- Removal of temporal spikes in sensor readings.

4.2 Data Transfer Optimization

Amount of data transferred between the iPhone device and the remote server impacts battery power and data usage cost. Since most users of the weBreathe application might have limited cellular data plan, our application is designed to use lower cost alternatives for network data transfer. When the user is registering a Node device, user is given a choice to transfer sensor data over 3G or only over Wi-Fi network. If the user has chosen Wi-Fi option, the data collected from sensor is temporarily cached in the local SQLite database on the device, if there is no Wi-Fi network available. The application receives notification from the iOS operating system if the network interface changes to Wi-Fi. Once the device is connected to Wi-Fi, the application transfers sensor readings in batches to reduce load on the server and as well as optimize battery energy usage. If the user chooses to use 3G/4G cellular data plan, the gathered data is transferred in batches every 5 minutes. The 3G download and upload rates for the various Cellular providers is shown below [9].

	Download(mbps)	Upload(mbps)
ATT	2.62	0.85
Sprint	0.59	0.56
T-Mobile	3.384	1.44
Verizon	1.05	0.75
Average	1.911	0.9

Figure 4-0-1 3G Speeds (mbps) for Major US Cellular Providers

According to Apple specifications, iPhone 4S has a Lithium-Ion battery with a capacity of 1420 mA-h. At 3.7 volts, it translates into 5.254 Watt-hours and could support Internet activity for up to six hours. IPhone 4S consumes 0.875 W (5.254/6) per hour for Internet activity. On an average of 1.9 mbps download rate, iPhone 4S could download 858 MB data per hour and at 0.9 mbps upload rate, it could upload 405 MB data per hour. weBreathe iOS application uses 300 bytes of data per sensor reading and could upload 1350000 readings per hour (405 MB/300 bytes). Our design balances to reduce the overhead associated with establishing a TCP socket connection and tearing it down, amount of data that can be transmitted in a single upload, time it takes to upload and processing overhead associated with large number of JSON array objects at the web services layer. If we assemble an array of 25 such sensor readings as an array of JSON objects and upload it during a single HTTP request, it takes 7.5 KB of data transferred in 66 milliseconds. We arrived at twenty five array size based on the calculations involving maximum number of readings possible if the user

Figure 4-0-2 weBreathe Energy Usage Analysis

travels at maximum of 65-75 mph and if we collect readings for every 0.25-mile interval. The iPhone system turns off Wi-Fi and cell radios when it detects a lack of activity. It is more energy efficient to transmit data in a shorter amount of time than continuously over longer periods of time.

Based on energy analysis using XCode instrumentation, there is direct correlation between data upload and energy usage. It is clear that smaller increases in energy usage are associated with smaller burst of data upload. Further data transfer optimization can be achieved by increasing time interval between data uploads and increasing batch size. But this would degrade the real time pollution data availability to other community members.

4.3 Data Transfer Cost Optimization

On an average, 3G cellular data plan cost $10 per 1GB of data transfer. If an average weBreathe application user monitors pollution data for eight hours per day for thirty days and if 7.5 K data is transmitted at the rate of every 5 minutes, the user would normally use 21.6 MB of cellular data plan, which translates to 21.6 cents of expense per month. We have implemented gzip algorithm to compress the sensor readings before it gets transmitted to the server. Tomcat server and Jersey Framework are custom configured to enable gzip compression support using jersey plugins. weBreathe iPhone application connects to tomcat server and notifies server that it supports gzip “Content-Encoding:gzip” and sends compressed data using gzip algorithm. Tomcat server acknowledges gzip support and decompresses input data using gzip.

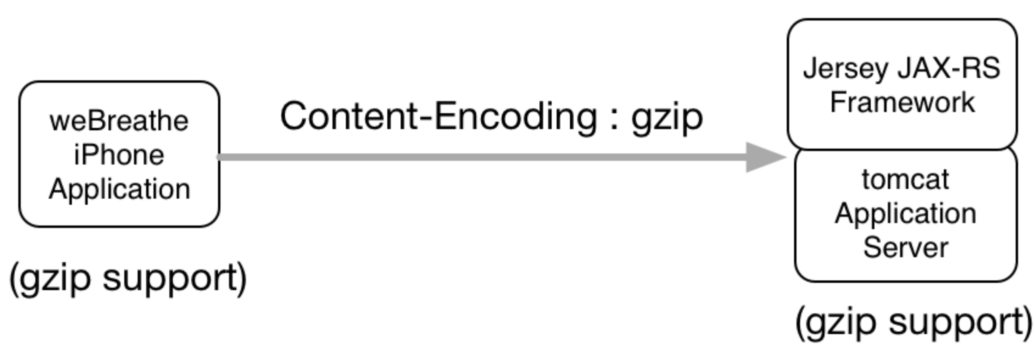


Figure 4-0-3 weBreathe uses gzip Compression to Reduce Data Plan Cost

GZIP compression works by finding similar strings within the JSON payload and replacing those strings temporarily to make overall payload smaller. This type of compression is well suited for the JSON payload because the key values are often repeated in a collection of sensor readings. GZIP employs deflate data compression algorithm that uses a combination of the LZ77 algorithm and Huffman coding. We have found with maximum gzip compression ratio used, the data payload size is reduced by 90%. The 7.5k JSON payload mentioned above, is reduced to 768 bytes, thereby reducing the cost of data plan usage by 90%, hence reducing the cost to almost 2 cents per month.

GZIP compression also reduces the battery energy consumption considerably because it transmits reduced amount of data per sync up cycle.

4.4 Pollution Map Display Optimization

The user interface to convey air pollution information along the roadways is the map display at the street level. We have used the MKMapView object to display the pollution data over the map view. User can zoom in or zoom out and move around the map display. The pollution information is dynamically retrieved from the remote web service. Each pollution record contains GPS coordinates (longitude, latitude) and pollutant AQI index. We have used MKPolyline object to connect these pollution coordinates as polyline with color-coding based on the AQI value. MKPolyline overlays over the roadways, thereby providing a graphical display of pollution levels to the user. The optimization techniques employed involves the following

1. Instead of displaying every point, combine nearby points based on pollution level
2. Use background threads to load data and display in batches
3. Display only those points that are visible on the map display
4. Cache overlays and reuse to reduce memory footprint.

We have evaluated Douglas-Peucker algorithm [45] to combine nearby points. The algorithm starts an edge with first and last points of the polyline; the remaining points are tested for the closeness to the edge. If there are points further away than specified tolerance level from the edge, then the point furthest from it is added to the polyline. This creates a new approximated polyline. Using recursion, this process continues for each point of the polyline until all points of the original polyline are processed.

In order to limit the number of points that can be displayed over the map, we have used spatial query with the PostGIS function ST_Intersect to retrieve points that are contained within the map max and min co-ordinates. It greatly improved the map display performance and reduced the amount of data that is retrieved from the webservice, thereby further optimizing energy efficiency of the application. MKOverlay objects are cached in memory and reused, thereby reducing the amount of memory needed to display pollution data as the user scrolls around the map display.

We also evaluated various GPS location update optimization techniques such as turning off location manager services when the user is not moving and reactivating location manager updates based on local accelerator movements.

4.5 Outlier Detection

Because of the initial settling time required for the various electrochemical gas sensors, they might show abnormal AQI values. It is important to detect such outlaying sensor readings. Usually such outliers are considered noise and thus need to be discarded in order to obtain a reliable pollution reading. One of the simplest outlier detection algorithms is Chauvenet's criterion [46], which uses the mean and standard deviation calculated from the sample to determine a "normal" range for values. Any value outside of this range is deemed an outlier.

The problem with Chauvenet's criterion is it assumes normal distribution of data values. Unfortunately, in our case, the pollution data varies by location and various environmental factors. One reasonable assumption we could make is pollution data follows a normal distribution in a specific geo location area, for example, area with in a zip code. We have adapted Chauvenet's criterion because of its simplicity but we limited our outlier removal based on the geo location points contained within the geometrical area of a zip code. For this we have used geo spatial database containing all zip codes in US and used ST_Contains PostGIS spatial query to retrieve all of the sensor readings obtained within an area covered by a zip code and applied Chauvenet's criterion to remove any outlier data. The outlier processor is implemented as part of server process that wakes up every three hundred seconds and runs in the background to mark any outliers. When data is retrieved from the app for diplay, the outliers are not pushed.

We believe zip code pollution data normalization is a reasonable assumption to remove any outliers and Chauvent's criterion proves to be an efficient algorithm to remove temporal spikes in sensor readings.

4.6 Speed Based Sensor Reading

Speed based data gathering involves enabling data collection only when the user is moving above a predetermined speed. In the situation where the iPhone automatically pairs with Node to start collecting data, we would want to avoid scenarios where the Node is static but the application repeatedly collects pollution data for the same location. Tracking the speed will determine the user in motion on the street and thus enforce data collection when device is in a vehicle travelling on the road. iOS Location Services (GPS) provide Speed parameter along with latitude and longitude values. Based on this speed value, we dynamically calculate the number of readings to be collected per time unit based on the assumption that we need pollution level readings at constant distances (for example, one reading per 0.25 mile). If the user is travelling at sixty miles of hour, we need to sample sensor readings at fifteen seconds interval so that we gather one pollution level reading every 0.25-mile.

Chapter 5

Evaluation

The purpose of this chapter is to discuss the evaluation of various components of mobile pollution sensing social model and to discuss the results from comparing pollution data from the mobile model with NJ DEP (Dept. of Environmental Protection) stationary central monitors. It starts with the goals of the evaluation approach. Then, it describes the data flow samples from various components, starting from node sensor to the iPhone application, then to the back end server and then back to an iPhone for consumption. It also illustrates calibration techniques used to arrive at baselines for CO sensors at EPA laboratory. Then, it describes the details of the field study from data captured using the mobile pollution-sensing model at and around NJ DEP stationary monitor at Newark, NJ. The results of the evaluation are then analyzed for accuracy and timeliness. In the final section, we explore the advantages of using such dynamic mobile sensing model and how it could augment the existing DEP stationary sensors.

5.1 Goals

For a mobile-based pollution model to be effective, the Node gas sensor should be sensitive enough to accurately detect varying pollutant levels in the atmosphere. The gas sensor should also have shorter settling times and they must be quick to detect pollutant gas levels as early as possible so that commuter is alerted in a timely fashion. The pollution data should also be available in real time to other users who are travelling on the same road or location. The application should perform efficiently to save battery power on the mobile device, reduce storage requirements on the server and optimize the amount data exchanged over the network. It should also be scalable to support thousands/millions of social community users. Our evaluation goal is to try to address these objectives to validate the feasibility and practicality of mobile sensing model.

The main goals of evaluation are:

1. Validate real time responsiveness of data exchange and sharing among other users.
2. Provide effective use of resources such as battery power, network bandwidth, storage and processing time.
3. Assure effectiveness of outlier detection.
4. Ensure accuracy and precision of Node sensors by calibration against standard gases
5. Field study of NJ DEP stationary central gas monitor vs. mobile pollution sensing monitors.

5.2 Real-time Responsiveness

In our model, exchanging real time pollution information with other users is vital for its operational success. Efficient data exchange and optimized network and data usage reduces the time lag between data generation and data consumption. The model has two modes of operation, monitoring and pollution map view modes.

Pollution Map View mode has the following set of operations

1. User Registration (One time)
2. Login
3. Pollution Map view

Monitoring mode has the following set of operations

1. User Registration (One time)
2. Device Registration (One time)
3. Baseline Calibration of Node Sensor (One time)
4. Login
5. Pollution Monitoring

We measured the performance of each operation based on the system clock time on the mobile device. The clock time includes CPU time, network round trip time and server processing time. Baseline calibration is performed using Node application named NodeOXA and it would take 5 mins an average per device for one time calibration of the baseline. Upon calibration, the baseline value is stored in the ROM memory of the Node device itself and can be queried by Node API. Based on the device logs, the average time for each of the operation is shown on the graph below

Figure 5-0-1 Execution Time for Operations

The execution time is dependent on various factors like network speed, load on the server and number of the concurrent users etc. We estimate each operation to take less than 1 sec under normal operating conditions and real time sharing of pollution data could happen within couple of seconds of uploading the data to other community users.

5.3 Outlier Detection

Outliers are deviant sensor readings away from the normal level of CO PPM expected in a certain geo location. Outliers could occur due to various reasons. In our prototype, we observed, the outlier readings are mainly due to initial settling time required for the gas sensor. When the monitoring is turned on in the node sensor, it starts with very high PPM readings and within a couple of minutes, it settles down and starts giving normal readings. We also observed it happens every time monitoring is turned off and turned on again. The other occasions we see sudden spikes in readings are when the sensor exposed to sudden high levels of CO, for example a heavy truck passing by and cold start of motor vehicles. The purpose of our study is not only to identify outliers and also arrive at an approach to manage them. We want to flag outliers due to sensor's initial settling at the client level and other types of outliers at the centralized back end server. Based on heuristic, we arrived at an initial settling count of readings that can be safely ignored when the node sensor is turned on for monitoring. We have designed a background process that periodically wakes up (every 5 minutes) and analyzes the latest readings recorded per geo location. In our case, we have chosen to use the geo location area covered by a US zip code. We have pre-populated all of the zip codes and its spatial dimensions (shape files) from census.gov website into our POSTGIS database table.

We have used Chauvenet's criteria as the basis for outlier detection.

Algorithm for zip code based spatial query for outlier detection:

1. Get all of readings recorded since the last run
2. Get a list of zip codes by applying spatial query ST_Contains to check if the longitude and latitude of the reading location falls within the zip code spatial dimensions.
3. Calculate the average and standard deviation of the all of the readings for each of the zip code.
4. Calculate complementary error function erfc [reading – average/std dev].
5. If the erfc value is less than 0.5 (1.96 std dev), flag the reading as outlier in the database.

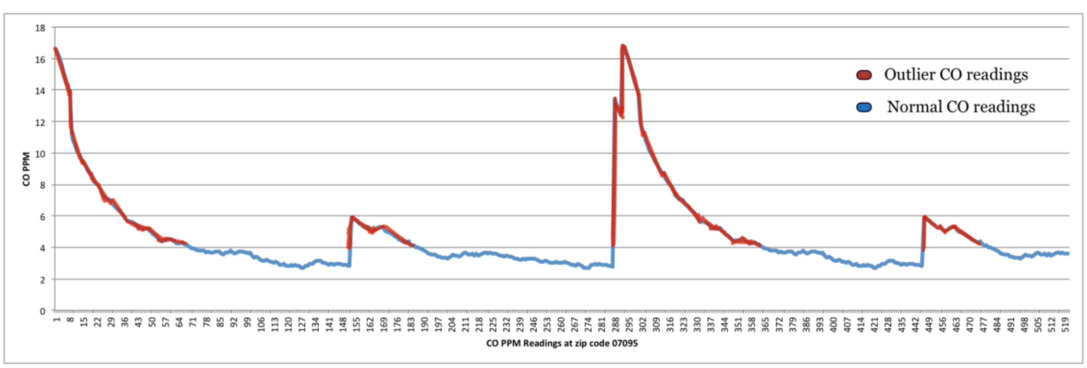


Figure 5-0-2 Outlier Detection

Any value marked as outlier is not displayed on the pollution map but the reading is retained in the database for further analysis.

For example for the zip code of 07095, the outliers are marked in the outliers region as shown.

As shown above in the figure 5-0-2, the outliers are illustrated with a color red. When the node device is turned on, the initial settling values are identified as outliers and not displayed on the pollution map. The intermitted spikes in values are correlated with turning on and off of the node device.

When outlier batch job is run, it picks up all of the new readings since its last run and applies the outlier detection algorithm for each of the zip code region that readings geo co-ordinates fall under. For example, the reading id 365204 with a ppm value of 13.879 is marked as an outlier for the zip code 07095 because it is more than 1.96 standard deviations of the other readings for the zip code location. The server log indicating outlier detected is included in Appendix A.

5.4 Data Flow Illustration

weBreathe iPhone application uses iOS Bluetooth framework to connect to the node sensor. Once it is connected, the user turns on monitoring by selecting the monitor button. Once the monitor button is selected, the application requests Node sensor to stream CO pollution readings at a predefined time interval (in units of 10 milliseconds). For example, weBreathe application uses 100 units as sense interval which means it requests updates every second. weBreathe application uses node API shared library to interface with node sensor. All of the API communication is based on call back mechanism. For example, when the Node module is ready for communication, it calls nodeDeviceIsReadyForCommunication method. Our iPhone application initializes Node device, queries for CO baseline reading, queries for all of the sensor modules on the device and once it receives callback, it refreshes the user interface with type of gas sensor modules and CLIMA module details for getting humidity and temperature details.

weBreathe application collects a predefined set of readings and uploads the readings as a gzip compressed JSON array to the backend server as a HTTP post. The phone log in Appendix B illustrates sensor data capture and transmission.

Due to the compression technique, we could see the original payload size of 5576 bytes is reduced to 594 bytes which around 90% savings in the data transmission. For example, in the picture shown, the storing of reading took four hundred ninety five milliseconds to execute. Our backend server (IP Address 165.230.44.85) runs a tomcat server at port 8080. Our server clock is skewed by -751 seconds than the mobile phone. The J2EE application Sensor_ReadingsService uses UserManagerServlet to record readings. The Server access log in Appendix C shows the client IP address, type of request, result of the request and how many milliseconds it took to complete the request.

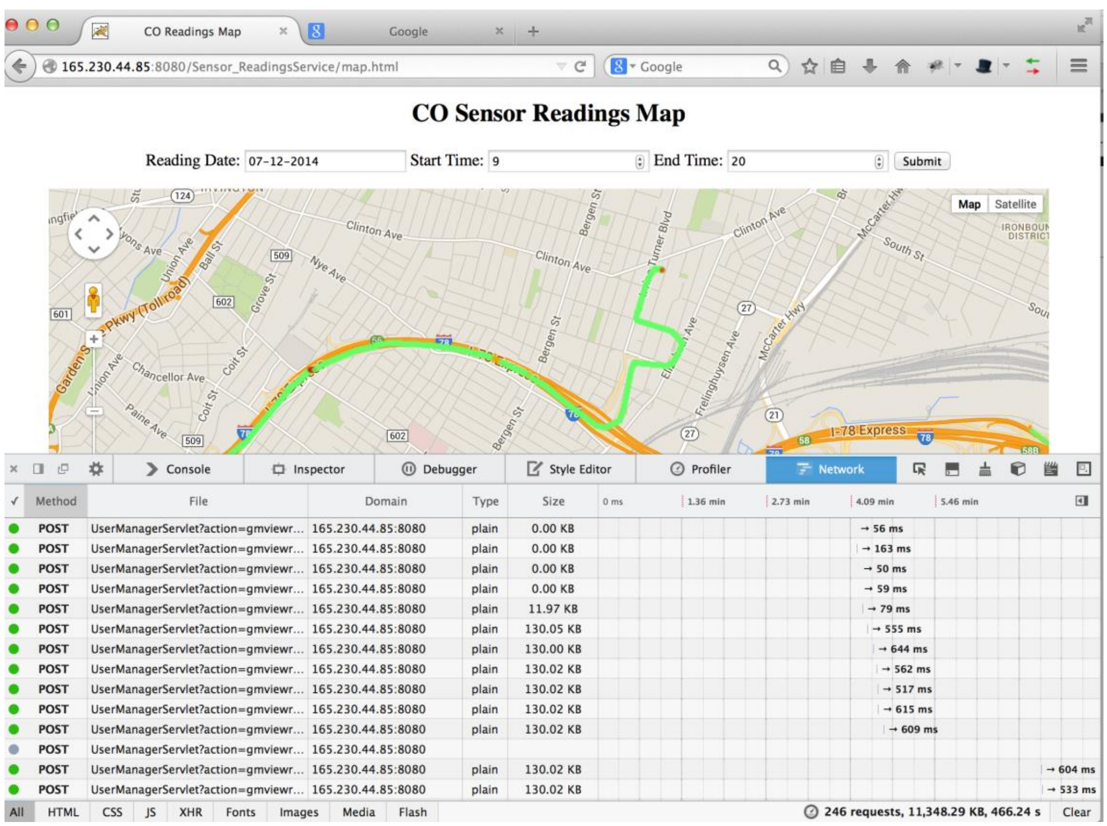


Figure 5-0-3 Map View and Response Data Illustration

The map view includes a server request specifying longitude and latitude of map view port corners, date, start and end time of the readings. For example, the http post request illustrated in Appendix D retrieves the readings bounded by the map view co-ordinates on the date of July, 12, 2014 between the hours 9 am to 8 pm. Based on the network performance profiling, such a request returns 135 K of data in less than six hundred milliseconds. The map view results don't contain any outlier data because the query filters out outlier readings. By limiting the number of readings to the geo location boundaries of the map view port, we are able to optimize the retrieval and map rendering performance to less than one second.

5.5 Calibration of Node Sensors

Calibration is the process of evaluating and adjusting the precision and accuracy of measurement equipment [36].Calibration of low-cost gas sensors improves overall accuracy of the sensor performance under ambient environmental conditions. Calibration of sensors helps reduce any error in readings, which are differences between actual values and sensor response values. Any such errors can be identified during the calibration process, and then used to compensate the sensor readings to arrive at actual ambient values.

Baselining:

Traditionally, calibration of gas sensors involves a two-step process [43]. The first step is zero calibration or baselining, followed by span calibration. Zero calibration or baselining involves recording [44] raw or PPM sensor reading in an atmosphere free of target gas, which in our case is an atmosphere free of CO. An electrochemical sensor's baseline is the difference in electrochemical current measured between the sensing and reference electrodes when exposed to zero gas [37].

Figure 5-0-4 Lab Setup for Baselining of Nodes

In Rutgers Environmental Science lab, a sealed container with valves, to ensure constant pressure within the enclosure, was used for the experiment. A CO free environment was created within the container by introducing argon gas for approximately fifteen minutes. This simulated a 0 ppm of CO environment. The raw values measured by the CO sensor in this simulated 0 ppm environment were noted, using the Node+OXA application, as the baseline, as shown in Fig 5-0-5. This same experiment was performed across six available Node sensors and was repeated seven times for each of the Nodes. Node sensor stores the baseline raw value in its memory so that it can be retrieved using Node API interface for PPM calculations in the mobile app. We also derived method detection limit, as shown in Appendix E, to ensure that the readings were not due to sensor noise and to establish the lowest CO concentration that can be measured using Node sensors.

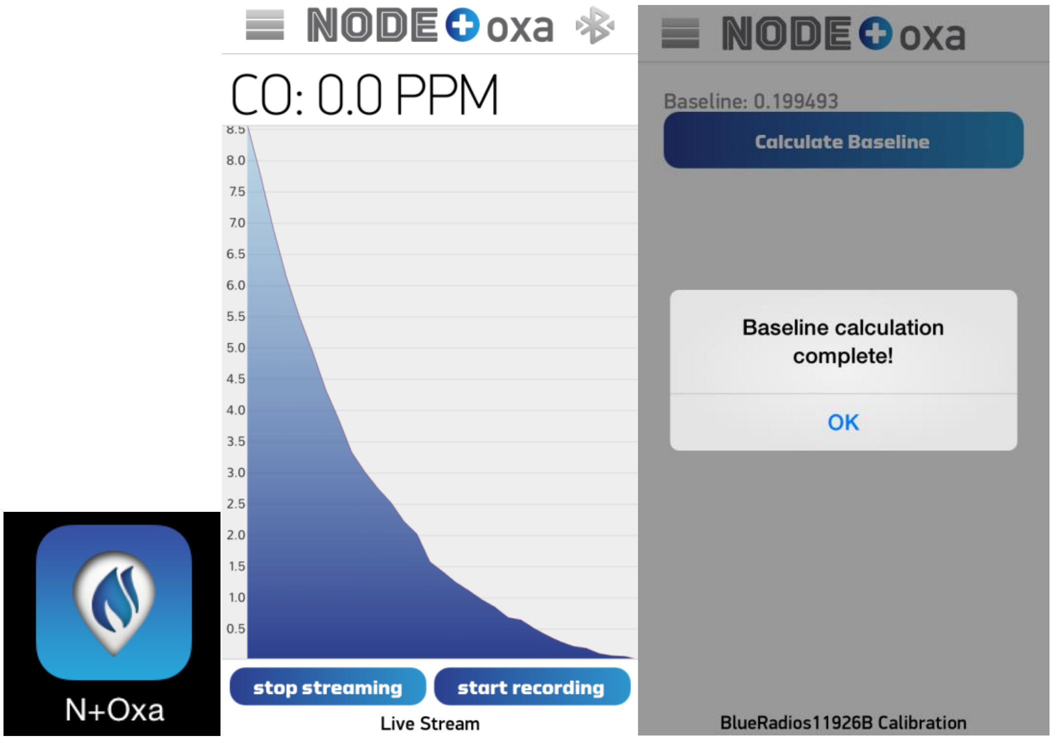


Figure 5-0-5 N+Oxa app for Baselining

Calibration:

The next step in calibration is span calibration, in which premixed calibrated gases are exposed to sensor and statistical methods in calibration are applied. In our study, six baselined Node sensors were used for the span calibration. We conducted the calibration experiments in EPA (Environment Protection Agency) lab in Edison, NJ. The baselined Nodes ensured that the sensors were capturing the most precise CO readings in ppm. Another larger enclosure to contain the Node sensors was used for this experiment. Different concentrations of CO gas were introduced into this chamber through a multigas calibrator- Environics Series 6100 Computerized Multi-Gas Calibration System and allowed to stand for 20 minutes. The calibration set up is shown in Fig 5-0-6 and Fig 5-0-7. The values captured from weBreathe application for CO level in ppm, temperature and humidity were recorded and regression analysis was performed.[39] (As shown in fig 5-0-8).

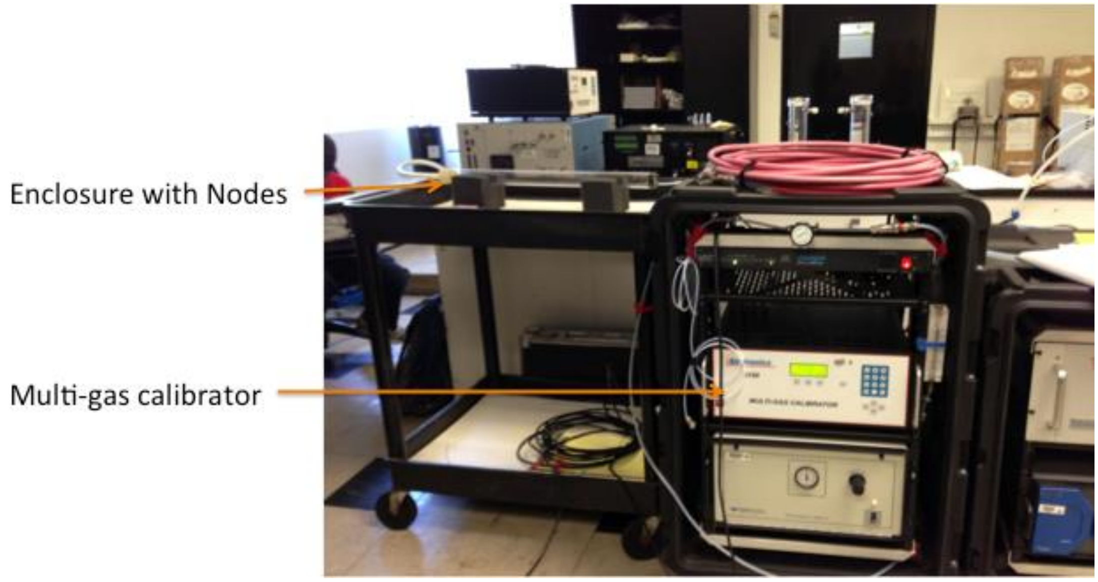


Figure 5-0-6 Calibration set up in EPA lab – Multi Gas Calibrator

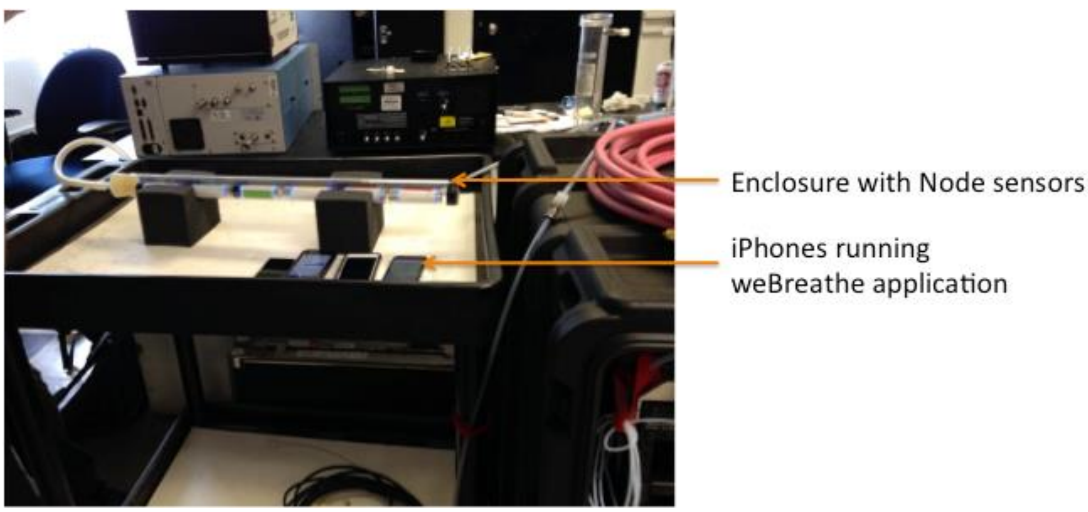


Figure 5-0-7 Calibration set up in EPA lab – Enclosure with Nodes

The calibration data collected from the above tests were used to derive the actual CO value in ppm from the values the Node sensors reported [38]. The calibration of two of the Nodes is represented in the Figure 5-0-9 and Figure 5-0-10 below.

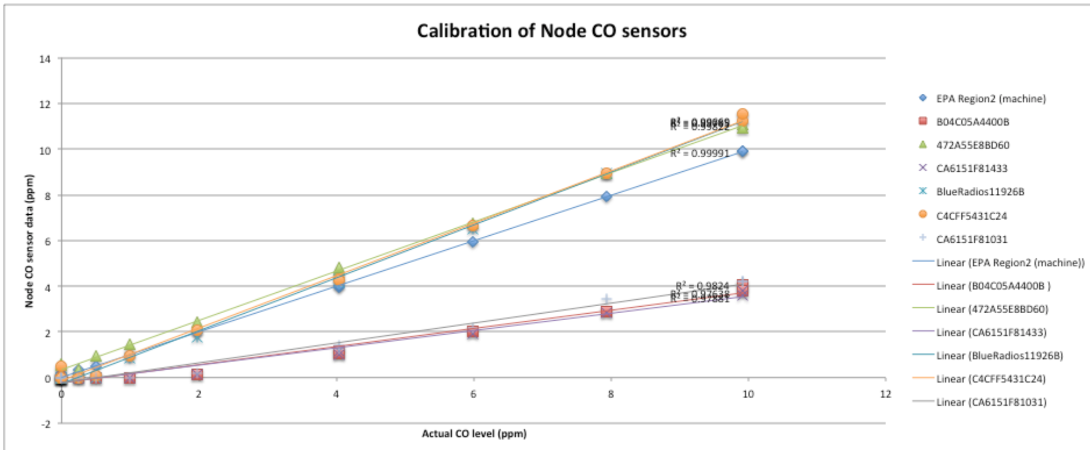
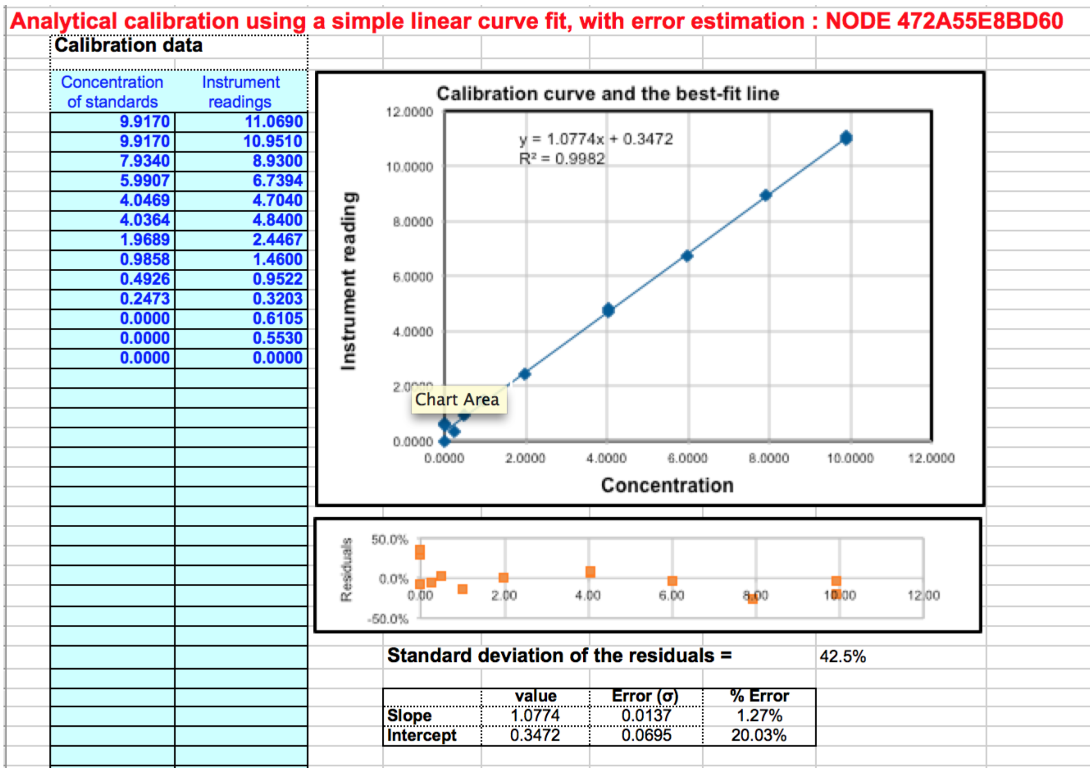


Figure 5-0-8 Regression Analysis of Calibration Data



Concentration of standards	Instrument readings
9.9170	11.0690
9.9170	10.9510
7.9340	8.9300
5.9907	6.7394
4.0469	4.7040
4.0364	4.8400
1.9689	2.4467
0.9858	1.4600
0.4926	0.9522
0.2473	0.3203
0.0000	0.6105
0.0000	0.5530
0.0000	0.0000

Standard deviation of the residuals = 42.5%

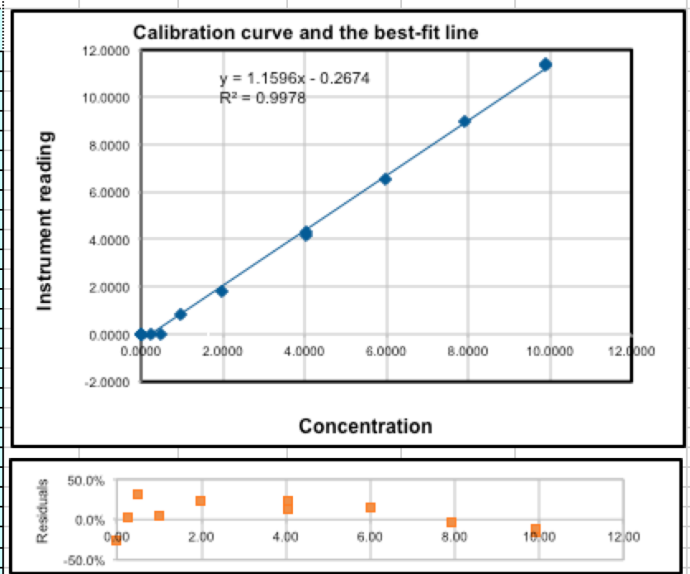
	value	Error (σ)	% Error
Slope	1.0774	0.0137	1.27%
Intercept	0.3472	0.0695	20.03%

Figure 5-0-9 Linear regression Node 472A55E8BD60

Analytical calibration using a simple linear curve fit, with error estimation : Node C4CFF5431C24

Calibration data

Concentration of standards	Instrument readings
9.9170	11.3940
9.9170	11.3507
7.9340	8.9691
5.9907	6.5227
4.0469	4.2978
4.0364	4.1740
1.9689	1.7784
0.9858	0.8391
0.4926	0.0000
0.2473	0.0000
0.0000	0.0000
0.0000	0.0000
0.0000	0.0000



Standard deviation of the residuals = 64.4%

	value	Error (σ)	% Error
Slope	1.1596	0.0162	1.40%
Intercept	-0.2674	0.0822	-30.75%

Figure 5-0-10 Linear regression Node C4CFF5431C24

Measurements gathered from Node devices were corrected by the inverse of the calibration curve. From plotting the data and applying linear regression statistics, the calibration equation (i.e., the gradient and the intercept) is used to estimate the concentration of CO in field studies [40].

Applying the calibration curve on values collected from Node sensor eliminates instrument bias provides accurate values when the sensor is deployed in the field. The actual values of CO in ppm derived for two of the Node sensors were as follows, from inversing the calibration graph:

NODE-472A55E8BD60 : actual_value = (Node reading - 0.3472)/1.0774

NODE-C4CFF5431C24 : actual_value = (Node reading + 0.2674)/1.1596

5.6 Study of Mobile Sensing Model Data in Comparison to Stationary Central Monitor

The calibrated Nodes were used for a field study conducted to compare our mobile pollution sensing model with existing central air pollution monitors. The objective of our field study is to demonstrate spatial granularity of pollution data along the roadways. As part of this analysis, we conducted a field study of pollution data collection using Node sensors inside a car, windows closed, as a typical commuter would do, driving along the road ways. We compared our results to pollution levels reported by a certified stationary monitor.

The Department of Environmental Protection in New Jersey (NJ DEP) has various central monitoring stations located across the state of NJ to monitor and predict air quality. These central monitoring stations have sensors for monitoring pollutants such as CO, O3, SO2, NO2 and PM 2.5[41]. The reports from these stations are available for public consumption via email, website or mobile application.

For our study, we chose the stationary monitoring station located at Newark Firehouse at Newark, NJ since it has a CO monitor that we could compare against and the location was easily accessible.

The primary goals of the study are

1. Compare central monitoring station data with data gathered from mobile pollution sensing social model.
2. Evaluate the precision and accuracy of data collected from mobile pollution sensing social model, using statistical analysis
3. Analyze spatial granularity of data at various distances at and around the stationary monitoring station.

Our study procedure involves collection of data at various roadways near the stationary monitor, apply calibration error correction to derive true CO concentration and analyze the data using statistical tools.

The first step in our study was to visit the NJ DEP Newark Firehouse monitoring station and collect readings by:

- Standing right next to the NJ DEP monitoring station with 3 Nodes and 3 iPhones running

Figure 5-0-11 NJ DEP Newark Firehouse Monitoring Station

weBreathe application

- Driving along the streets adjacent to the NJ DEP monitoring stations with two Nodes placed near vent inside car using weBreathe application on two iPhones

- Driving along streets that were approximately 0.5 miles away from the NJ DEP monitoring station with two Nodes placed near vent inside car using weBreathe application on two iPhones

- Driving along streets that were approximately 2 miles away from the NJ DEP monitoring stations with two Nodes placed near the vent inside car using weBreathe application on two iPhones.

The next steps for evaluation of data collected were (represented in Fig 5-0-13, Fig 5-0-14, Fig 5-0-15 and Fig 5-0-16 below):

- Applying calibration function on data collected from Nodes.

- Splitting data collected into segments of 60 second intervals so there were greater than thirty

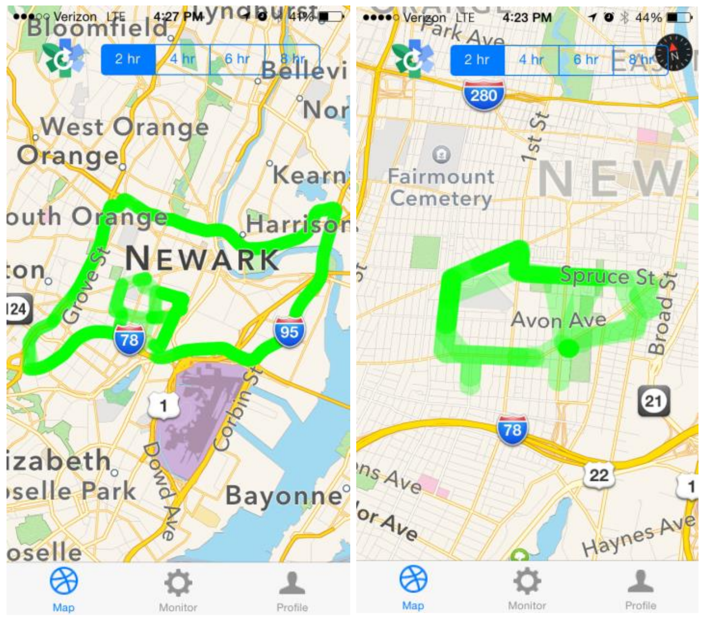


Figure 5-0-12 weBreathe iOS app Displaying Pollution Levels Around NJ DEP Station

samples in each segment across three Nodes(if sample size is large (n>=30), then the sample standard deviations can be used to estimate the population standard deviation)[42]. This enables us to study the distribution of pollution data among monitors and distribution across distance.

- Calculating the mean CO level for each segment of data

- Calculating standard deviation and margin of error for each set of data, averaged over a time period of 60 seconds and over the same distance from central monitor

- Plotting the NJ DEP monitor CO level to compare against the pollution data captured from mobile pollution sensing model

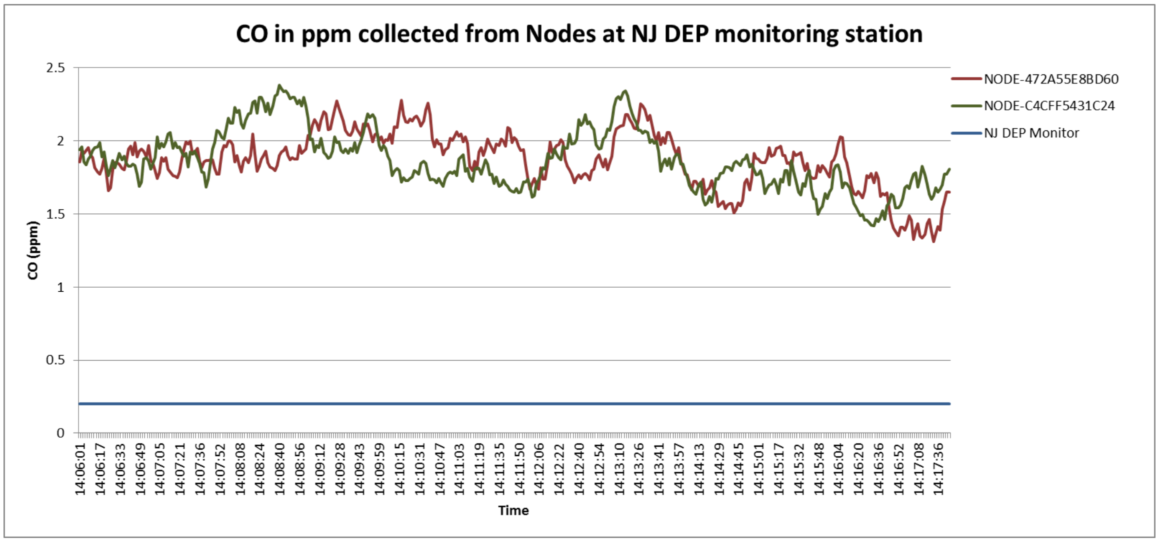


Figure 5-0-13 Mobile Pollution Sensing Data at NJ DEP Monitoring Station

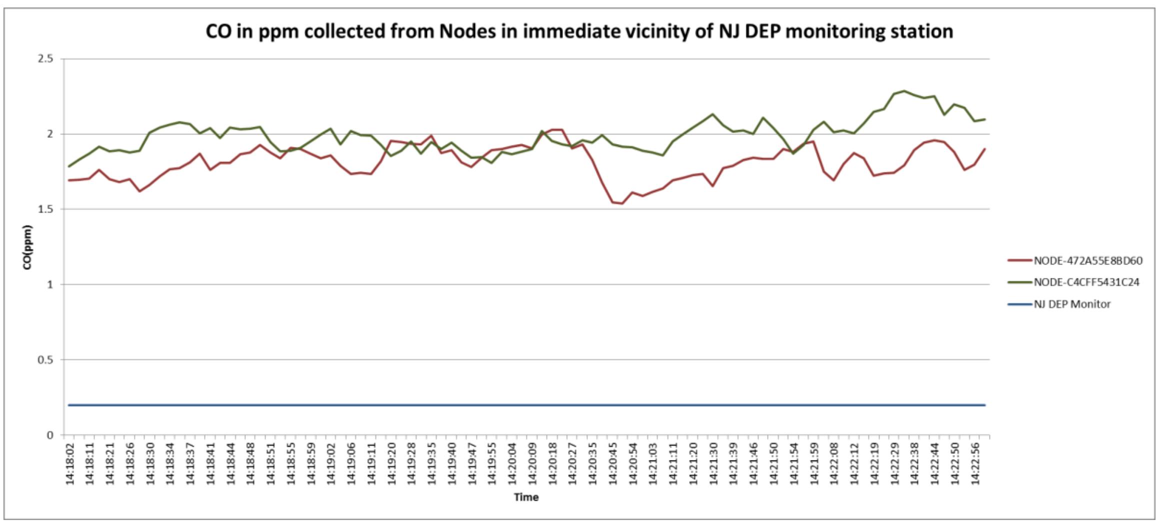


Figure 5-0-14 Mobile Pollution Sensing Data at Immediate Vicinity of NJ DEP Monitoring Station

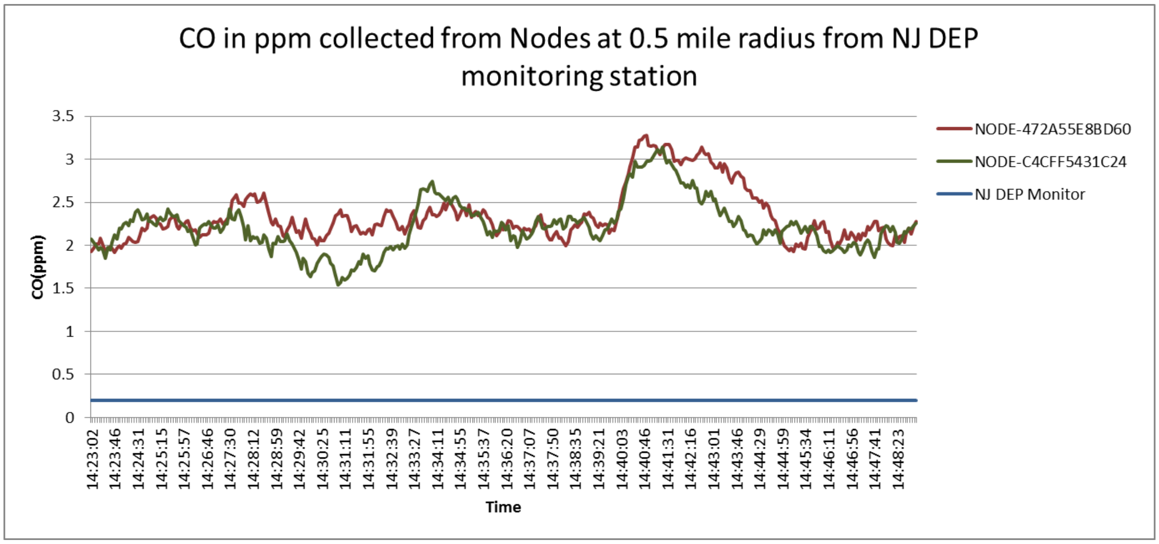


Figure 5-0-15 Mobile Pollution Sensing Data at 0.5 mile Distance from NJ DEP Monitoring Station

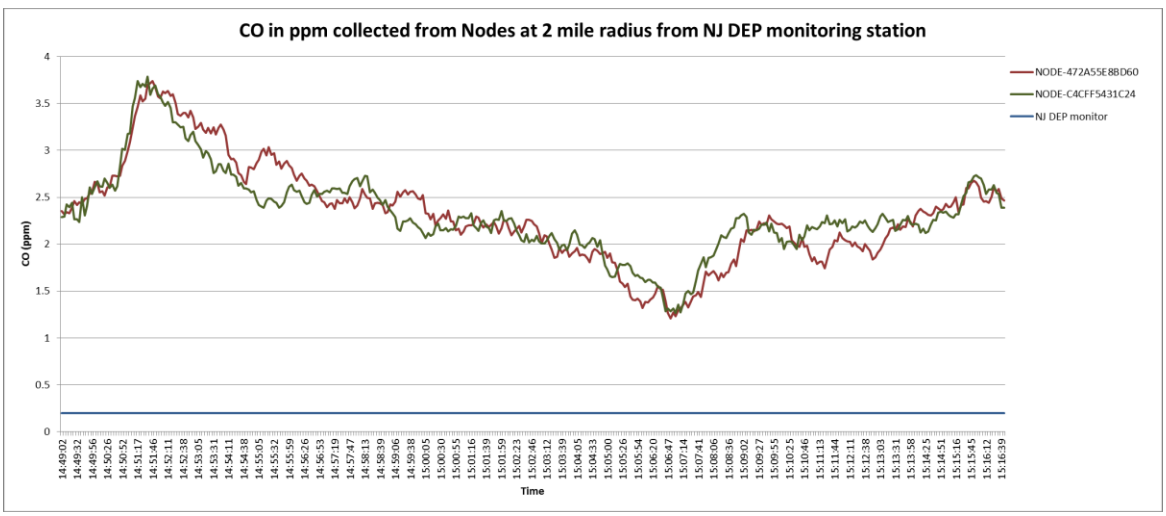


Figure 5-0-16 Mobile Pollution Sensing Data at 2 mile Distance from NJ DEP Monitoring Station

Conclusions from field study:

- Calibration against standard gases and linear regression analysis applied to data demonstrates accuracy of data collected
- Data collected from mobile pollution sensing model demonstrates spatial granularity of air pollution along roadways

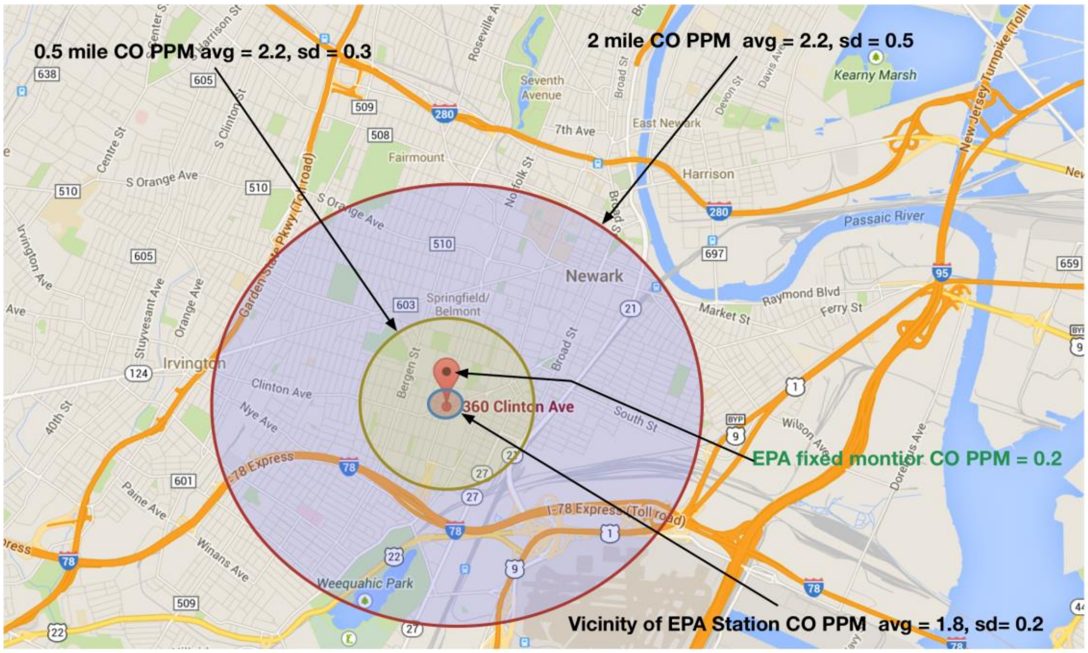


Figure 5-0-17 Map summarizing spatial granularity of pollution data

- Mobile pollution sensing model effectively captures the spatial granularity of pollution data and provides timely representation of air pollution to commuters.

Chapter 6

Future Directions

In this chapter, we present several areas of further research that can be explored in order to expand the work proposed by this thesis. We first discuss how we need to device appropriate sensor maintenance techniques to ensure the quality of data. We then discuss how we can apply some mechanisms to address privacy concerns of users sharing pollution data. This is followed by discussion of the various enhancements and optimizations that could be incorporated into the iOS application and backend server to personalize usage of the app as well as adding additional features to improve the efficiency and effectiveness of the data provided to users. Subsequently, we present how this model can be effectively used as the means to conduct various studies related to air pollution. We then discuss how the mobile pollution sensing model could lay a foundation for cleaner route guidance as well as eventually be incorporated in the larger scope of vehicular networks.

6.1 Sensor Maintenance

The calibration techniques mentioned in section 5.5 will ensure the quality of data measured using the mobile pollution-sensing model. But subsequent periodic calibrations are required to ensure quality of measured data using the mobile platform[48] . We need to arrive at techniques to enable members of the mobile pollution sensing social community to periodically calibrate their devices against a reference-calibrated device. Sensor decay, where the sensor degrades with time, is another issue to be addressed. We could use techniques where the mobile app will runs regular checks to ensure that the sensor is performing accurately and give alerts when recalibration of sensor or replacement of sensor is required.

6.2 User Privacy

Since our model involves sharing the air quality information along the streets on a map, we need to address any privacy concerns of users participating in our model. This would be addressed as the amount of data coverage is improved by high level of participation from the members since it will be difficult to track the routes of any particular participant collecting pollution data. Applying techniques such as removing the first and the last mile in the readings gathered will ensure that even if there are few users collecting pollution data in a certain location, it will not be feasible to see the precise locations that the user travelled.

6.3 iOS Application and Backend Improvements

Cumulative exposure alert: The application could be improved by the calculation of cumulative pollutant exposure of user in a day. As per the EPA standard, 36 FR 8186[10] CO exposure standards were set at 9 parts per million (ppm), as an eight hour average, and 35 ppm, as a one hour average, neither to be exceeded more than once per year. The average driver is not aware of the extent of cumulative exposure to air pollutants. Especially, for a user that spends a lot of time travelling on the roads, this would prove to be very valuable information. The application could calculate the cumulative exposure of the user and alert users.

Social networks integration: Social network integration could be added to the iPhone application enabling the user to share pollution data or pollution map snapshot posting over Facebook or Twitter like applications. This would not only motivate the users to collect more data, but also encourage friends and followers on these social networking sites to connect, collaborate and share air quality data.

Multiple device support: Currently our social model and iOS application supports the use of Node sensors. This can be easily expanded to enable usage of multiple gas sensors from different vendors. The app could be customized based on the sensor device that it is paired with.

Redundant data elimination: On the backend server, we could implement further optimization by tracking multiple users collecting data on the same road segment within the same time frame and enable push notifications to the devices from the server to stop collecting duplicate data. When it is detected that the user has moved to a new road segment, the monitoring could be restarted. These optimizations would further reduce redundant data usage and also conserve energy.

Multiple reading: A different approach that could be taken to handle multiple data points from the same road segment would be to utilize the multiple readings to arrive at the most accurate pollution level for that region. Removal of outliers from readings for same region would verify the accuracy of the pollution data.

Archive historic data: Another possible optimization on the server database would be to archive any stale data. Say all the readings that are more than a day old could be compressed and archived. Also, an eight hour average of pollutant level could be extracted from historic data and used to demonstrate pollution trends for various road segments.

Incorporate EPA data: The data presenting in the application is the pollution data collected from participating users of the social community alone. Incorporating data collected from various other air pollution monitoring systems can broaden the coverage. The EPA, for instance, maintains a repository of ambient air quality data in the Air Quality System (AQS). We could include a backend service to regularly pull the AQS data incorporate it with the data collected from the social community. The weBreathe app can then display the data from AQS for regions where no participating users have collected air quality data.

6.4 Data Studies

Using the mobile pollution-sensing model presented in this thesis, air pollution data could be collected for various studies. How air quality is affected by meteorological factors such as wind speed, temperature, humidity, pressure and climatic factors could help in creating prediction models for air pollution. Further studies could be conducted to find correlation between traffic patterns, vehicle speed and air pollution. Studies could be conducted to model the pollution propagation from point of emission and distribution to nearby locations. An interesting study could be conducted to compare the pollution levels inside the car with the ambient pollution level just outside the car.

Machine learning techniques could be applied to predict future pollution levels based on historic data collected using the mobile pollution-sensing model. Such predictive models can be used to make future city and roadway grid planning decisions. A user study can be conducted to analyze how the air quality information provided by our model impacts the behavior of users. It would be interesting to note how many commuters actually take alternate clean routes at the cost of additional travel times.

6.5 Green Routing

The launch of solutions such as Car-Play by Apple is a clear indicator of how connected vehicles would be in the near future. The addition of air pollutant sensors incorporated within motor vehicles does not seem a distant possibility. The vehicles in-built sensor technology combined with solutions such as Car-Play and ubiquitous Internet connectivity would enable us to provide highly accurate, real-time air pollution data with extensive coverage. We would be able to easily assimilate the air quality data over traffic maps to enable route guidance based on cleaner routes. An interesting study could be conducted on human behavior to analyze how often commuters actually choose to take a cleaner route by compromising travel time. Another approach to available pollution data is that altruistic citizens might even avoid heavily polluted streets so they can avoid causing higher pollution.

Chapter 7

Conclusion

In this thesis, we introduced the design and implementation of a mobile pollution sensing social community to enable the gathering and sharing of air quality data. We proposed a model that overcomes the shortcomings of current pollution monitoring methodologies. The design of the model involved selection of an appropriate device to measure pollutant levels and interfacing it with a smart phone application. By connecting a cloud service to a mobile application, we presented the feasibility of a real time pollution collection and sharing social model. By applying various optimization techniques at the application and web service level, we were able to make the model highly efficient and cost effective.

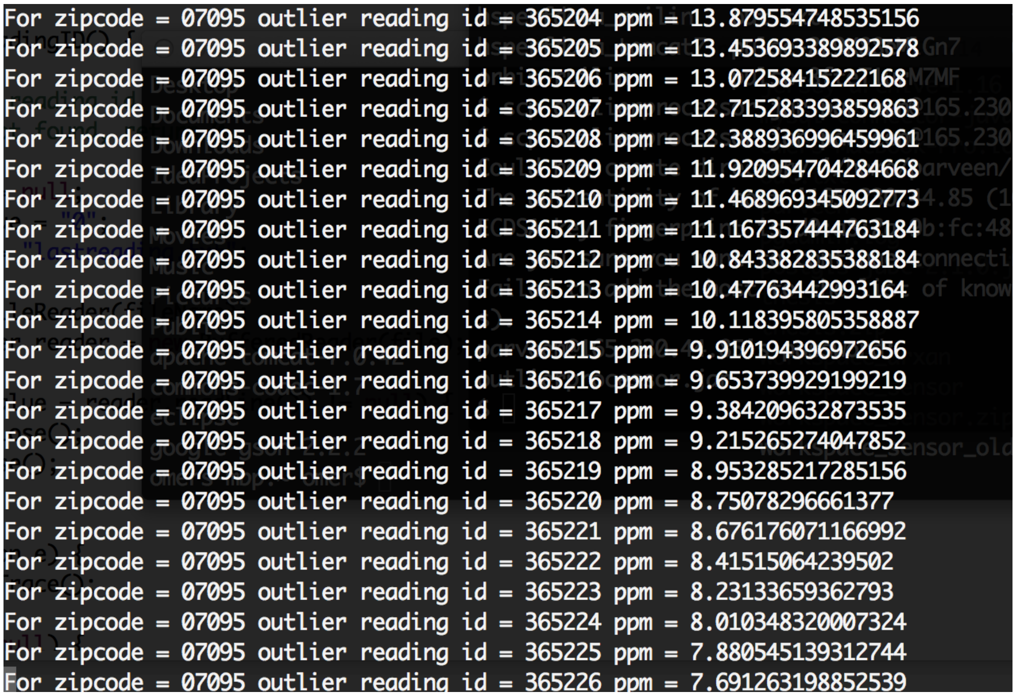
The key conclusions of this thesis are:

- Real time pollution information sharing is practical with adoption of mobile-cloud integration
- Highly efficient location data management can be achieved with the aid of spatial data model
- Optimized use of mobile battery energy is feasible with data compression and efficient location based data exchange
- We could use the model to collect data for both internal and external to motor vehicles
- Simple online social community model can be realized with two groups of members, consumers and producers.
- Mobile pollution sensing model captures spatial granularity of pollution data.

In this current day and age, smartphones are an integral part of our lives and put immense computing power and connectivity in the hands of users, thereby opening up a world of opportunities. Leveraging this technology to connect citizens with the common interest of air pollution awareness provides a highly practical solution to gather fine-grained air quality data. The increased adoption rate of this social community would translate into making the pollution data highly accurate and precise.

The applications of the data collected from our model is innumerous, starting from users utilizing it to guide their travels every day, to sensitive commuters avoiding more polluted routes. On a larger scale, the data could prove valuable in making informed decisions even for establishing schools or residential communities. This model opens the doors for exploring innovative opportunities to create a cleaner world.

Appendix A
Server Logs Indicating Outlier Detection



```
For zipcode = 07095 outlier reading id = 365204 ppm = 13.879554748535156
For zipcode = 07095 outlier reading id = 365205 ppm = 13.453693389892578
For zipcode = 07095 outlier reading id = 365206 ppm = 13.07258415222168
For zipcode = 07095 outlier reading id = 365207 ppm = 12.715283393859863
For zipcode = 07095 outlier reading id = 365208 ppm = 12.388936996459961
For zipcode = 07095 outlier reading id = 365209 ppm = 11.920954704284668
For zipcode = 07095 outlier reading id = 365210 ppm = 11.468969345092773
For zipcode = 07095 outlier reading id = 365211 ppm = 11.167357444763184
For zipcode = 07095 outlier reading id = 365212 ppm = 10.843382835388184
For zipcode = 07095 outlier reading id = 365213 ppm = 10.47763442993164
For zipcode = 07095 outlier reading id = 365214 ppm = 10.118395805358887
For zipcode = 07095 outlier reading id = 365215 ppm = 9.910194396972656
For zipcode = 07095 outlier reading id = 365216 ppm = 9.653739929199219
For zipcode = 07095 outlier reading id = 365217 ppm = 9.384209632873535
For zipcode = 07095 outlier reading id = 365218 ppm = 9.215265274047852
For zipcode = 07095 outlier reading id = 365219 ppm = 8.953285217285156
For zipcode = 07095 outlier reading id = 365220 ppm = 8.75078296661377
For zipcode = 07095 outlier reading id = 365221 ppm = 8.676176071166992
For zipcode = 07095 outlier reading id = 365222 ppm = 8.41515064239502
For zipcode = 07095 outlier reading id = 365223 ppm = 8.23133659362793
For zipcode = 07095 outlier reading id = 365224 ppm = 8.010348320007324
For zipcode = 07095 outlier reading id = 365225 ppm = 7.880545139312744
For zipcode = 07095 outlier reading id = 365226 ppm = 7.691263198852539
```

Appendix B
Phone Logs Illustrating Sensor Data Capture and Transmission

```
2014-07-01-09:19:10 Current Sense interval = 100.000000
2014-07-01-09:19:10 Current Batch size = 10
2014-07-01-09:19:10 Internet connection 3G available
2014-07-01-09:19:10 Internet connection 3G available
2014-07-01-09:19:10 Internet connection not available
2014-07-01-09:19:10 Internet connection 3G available
2014-07-01-09:19:10 notifiedThatNodeDeviceIsReady
2014-07-01-09:19:12 nodeDeviceIsReadyForCommunication
2014-07-01-09:19:13 nodeDeviceDidUpdateModuleSubTypes called
2014-07-01-09:19:13 OXA baseline = 0.199435
2014-07-01-09:19:13 nodeDeviceDidUpdateModuleSubTypes called
2014-07-01-09:19:13 OXA baseline = 0.199435
2014-07-01-09:19:14 Before Monitor Battery level 95.00
2014-07-01-09:19:14 Speed on location update= 1.88
2014-07-01-09:20:37 Raw reading = 0.199976
2014-07-01-09:20:37 ppm = 1.723120

2014-07-01-09:20:38 Raw reading = 0.199806
2014-07-01-09:20:38 ppm = 1.622736

2014-07-01-09:20:39 Raw reading = 0.200707
2014-07-01-09:20:39 ppm = 1.707382

2014-07-01-09:20:40 Raw reading = 0.200215
2014-07-01-09:20:40 ppm = 1.687971

2014-07-01-09:20:41 Raw reading = 0.200369
2014-07-01-09:20:41 ppm = 1.700468

2014-07-01-09:20:42 Raw reading = 0.200198
2014-07-01-09:20:42 ppm = 1.678569

2014-07-01-09:20:43 Raw reading = 0.200218
2014-07-01-09:20:43 ppm = 1.662803

2014-07-01-09:20:44 Raw reading = 0.199210
2014-07-01-09:20:44 ppm = 1.452895

2014-07-01-09:20:45 Raw reading = 0.199921
2014-07-01-09:20:45 ppm = 1.401922

2014-07-01-09:20:46 Raw reading = 0.200202
2014-07-01-09:20:46 ppm = 1.410717
```

2014-07-01-09:20:46 Original Payload =
[{"environment_Light":0,"reading_PPM":1.72312,"reading_interior_exterior_flag":"E","reading_travelling_vehicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_Atmospheric_Pressure":0,"device_Name":"NODE-472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200323,"reading_Time":"09:20:37","aqi":19.580906,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01 09:20:37"},{"environment_Light":0,"reading_PPM":1.622736,"reading_interior_exterior_flag":"E","reading_travelling_vehicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_Atmospheric_Pressure":0,"device_Name":"NODE-472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200271,"reading_Time":"09:20:38","aqi":18.440187,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01 09:20:38"},{"environment_Light":0,"reading_PPM":1.707382,"reading_interior_exterior_flag":"E","reading_travelling_vehicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At

mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200314,"reading_Time":"0
9:20:39","aqi":19.402073,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01
09:20:39"},{"environment_Light":0,"reading_PPM":1.687971,"reading_interior_exterior_flag":"E","reading_travelling_ve
hicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-
74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At
mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200304,"reading_Time":"0
9:20:40","aqi":19.18149,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01
09:20:40"},{"environment_Light":0,"reading_PPM":1.700468,"reading_interior_exterior_flag":"E","reading_travelling_ve
hicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-
74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At
mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200311,"reading_Time":"0
9:20:41","aqi":19.323505,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01
09:20:41"},{"environment_Light":0,"reading_PPM":1.678569,"reading_interior_exterior_flag":"E","reading_travelling_ve
hicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-
74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At
mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.2003,"reading_Time":"09:2
0:42","aqi":19.07465,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01
09:20:42"},{"environment_Light":0,"reading_PPM":1.662803,"reading_interior_exterior_flag":"E","reading_travelling_ve
hicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-
74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At
mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200291,"reading_Time":"0
9:20:43","aqi":18.895489,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01
09:20:43"},{"environment_Light":0,"reading_PPM":1.452895,"reading_interior_exterior_flag":"E","reading_travelling_ve
hicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-
74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At
mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200183,"reading_Time":"0
9:20:44","aqi":16.510172,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01
09:20:44"},{"environment_Light":0,"reading_PPM":1.401922,"reading_interior_exterior_flag":"E","reading_travelling_ve
hicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-
74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At
mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200157,"reading_Time":"0
9:20:45","aqi":15.930936,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01
09:20:45"},{"environment_Light":0,"reading_PPM":1.410717,"reading_interior_exterior_flag":"E","reading_travelling_ve
hicle_type":"car","device_ID":"5DD8F0C0-49BD-67AA-B895-BBDAA916CE2D","gps_Longitude":-
74.360055,"reading_ID":"0","environment_Temperature":0,"gps_Latitude":40.512153,"gas_Type":"CO","environment_At
mospheric_Pressure":0,"device_Name":"NODE-
472A55E8BD60","reading_travelling_flag":"y","username":"aaa@aaa.com","reading_Raw":0.200162,"reading_Time":"0
9:20:46","aqi":16.030872,"environment_humidity":0,"gps_Speed":1.88,"reading_Date":"2014-07-01 09:20:46"}]
2014-07-01-09:20:46 Original Payload size = 5576
2014-07-01-09:20:46 Compressed Payload size = 594
2014-07-01-09:20:46 Compressed Payload = <1f8b0800 00000000 0203ed98 5fabda30 18c6bfca e8f56979 f33ff16a ad753038 3b4736ef c62841b3 1ab0d5b5 d14dc6f9 ee8b1e8f 76630585 42bde845 2124799f e44d7e3c 49faf577 60ca9dad d665614a 973dda7c e982113c 0495d10b 5be6d974 fa2918a1 486082f0 a5d696ce 54765d65 e6d7a9f0 7da5f360 144c824b 2757e99d 59ad0ec5 9d59daf9 ca646ebf 31bed75c 57bedfc2 ececdc64 1f535fc3 d2547e80 31845425 69c8451c 8789542c 4c92348e 15e2e309 4e7d48be a9b3c775 995bb75d 78a150d0 887000c6 2ea31ee5 c0f76de6 3533c5c6 54da6d2b 73cceea8 a3dd4986 42c41046 8cf8065d 67b3d749 8e9fff11 895db1ae 374b9fef 3c9b56a6 aedfd44e 893ce9e2 10f7f49c 4e422a70 ccd84426 2987ff2f c969c1f6 be755b9b aa7c0dd6 5abff75f 345f178d b0cffaa7 1f28c200 04934bf5 cc1e6340 8d308c88 f001fa87 f5bba522 264101ff 7bfacb6d 6117d6ed cf0bf065 63cce2b0 b9525e34 53ed0e9a 18100d41 8480de9d e55f1eae 8485632c 081f68e9 9d162c50 1b2df24c 8b8c2805 2445a7b4 c8eb6911 20881cbc e50ebc05 d1365a54 c35b2860 bf639dd2 a26ef016 295493ea 8196be68 81365a28 34684112 51d5252c 5efd066b 01cae500 cb1d584b db414451 03167fbb 61c03aa5 05dd602d 4232ae06 5afaa7a5 8d15dc60 0504e5dd a2826f40 8563d99c e6804a5f 375cd56a 2ca471c3 f54b4765 b7c710b9 9e16cab0 9fc0404b efb420d9 6a2df44c 0bf7e900 12b8535a e80db400 5278780f dd012d4c b4d1c2ce b4b04811 50a4d37f 2d5efe7a 5a100824 065afaa7 85e3365a 78c35bfc bb4976ec 2d3c78f9 f607759b 039ec815 0000>
2014-07-01-09:20:47 StoreReading Post Execution time: 495.561004

Appendix C
Server Logs Illustrating Response Time

```
70.192.128.238 - - [01/Jul/2014:09:05:30 -0400] "POST /Sensor_ReadingsService/Us
erManagerServlet HTTP/1.1" 200 70.192.128.238   3 251
70.192.128.238 - - [01/Jul/2014:09:05:33 -0400] "POST /Sensor_ReadingsService/Us
erManagerServlet HTTP/1.1" 200 70.192.128.238   3 9860
70.192.128.238 - - [01/Jul/2014:09:05:33 -0400] "POST /Sensor_ReadingsService/Us
erManagerServlet HTTP/1.1" 200 70.192.128.238   3 10256
70.192.201.249 - - [01/Jul/2014:09:08:50 -0400] "POST /Sensor_ReadingsService/Us
erManagerServlet HTTP/1.1" 200 70.192.201.249   3 154
70.208.76.255 - - [01/Jul/2014:09:09:05 -0400] "POST /Sensor_ReadingsService/Use
rManagerServlet HTTP/1.1" 200 70.208.76.255   2 4
```

Appendix D
Map View Request

```
http://165.230.44.85:8080/Sensor_ReadingsService/UserManagerServlet?action=gmviewreadings
&minlon=-74.2440043975464&minlat=40.70013456990322&maxlon=-74.17096248165285&maxlat=40.72622295425412
&readingdate=07-12-2014&starthour=9&endhour=20
```

[{"gas":"CO","ppm":"2.824876070022583","aqi":"32.10086441040039","
longitude":"-74.24118041992188","latitude":"40.70498275756836"},{"gas":"
CO","ppm":"7.760548114776611","aqi":"83.60547637939453","longitude":"-74
.23893737792969","latitude":"40.70518112182617"},{"gas":"CO","ppm":"2.
8160240650177","aqi":"32.00027084350586","longitude":"-74.23956298828125
","latitude":"40.70512008666992"},{"gas":"CO","ppm":"7.0171051025390625"
,"aqi":"76.1710433959961","longitude":"-74.23731994628906","latitude":"
40.70551300048828"},{"gas":"CO","ppm":"5.920352935791016","aqi":"65.
20352935791016","longitude":"-74.23735046386719","latitude":"40.
70552444458008"},{"gas":"CO","ppm":"5.655942916870117","aqi":"62.
55942916870117","longitude":"-74.23636627197266","latitude":"40.
70577621459961"},…]

Appendix E
Method Detection Limit

BlueRadios119268	B04C05A4400B	C4CFF5431C24	CA6151F81433	472A55E8BD60	CA6151F81031
0.199496	0.202128	0.199137	0.200871	0.199807	0.200649
0.199679	0.202134	0.199135	0.200893	0.199979	0.200738
0.199587	0.202121	0.199057	0.201023	0.199823	0.200634
0.199612	0.202281	0.199468	0.200851	0.199727	0.200763
0.199425	0.202198	0.199176	0.200929	0.199633	0.200792
0.199479	0.202089	0.199054	0.200903	0.199565	0.200678
0.199493	0.202096	0.19894	0.200837	0.199435	0.200659
7.97E-09	4.61E-09	2.72E-08	3.87E-09	3.29E-08	3.83E-09
sum of variances above:		8.03772857142846 × 10^-8			
pooled variance:		1.3396214285705 × 10^-8			
pooled standard deviation:		0.000115742			
T value at 5 degrees of freedom and a=.01: 3.365					
calculated MDL:	**0.00038947188410109*				
*rounded at the end of all calculations					
Steps to Calculate the MDL					
The formula is:	$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$				

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