United States Environmental Protection Agency

Open-source, networked lead sensor modules

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U.S. EPA P3 PEOPLE PROSPERITY PLANET

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Introduction

Lead is a known cause of neurological and developmental maladies, particularly in infants and small children (Triantafyllidou and Edwards 2012). The presence of lead in lead service lines (LSLs) and premise plumbing continues to be an important exposure pathway. As a result, the Environmental Protection Agency (EPA) has set the maximum contaminant level (MCL) of lead to be zero and the action level of lead to be 15 ppb. The Lead and Copper Rule Revisions were finalized in 2021 and set an additional trigger level of 10 ppb that will require municipalities to reevaluate their corrosion control and lead service line replacement strategies (EPA 2021).

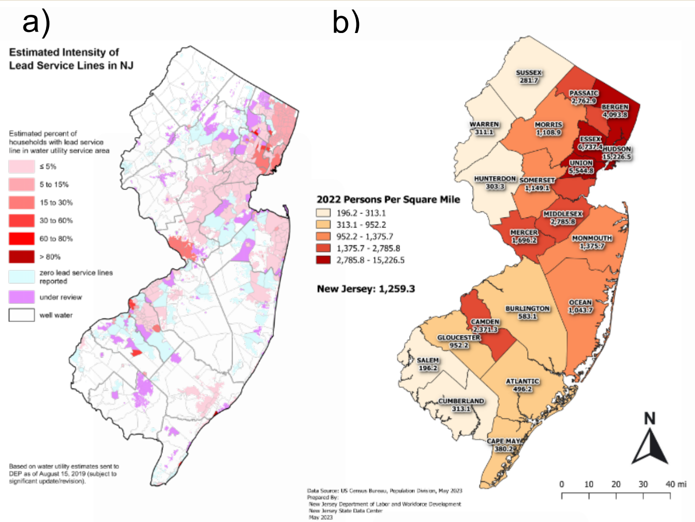

Figure 1 Map of New Jersey (a) Households with lead service line (Brune, 2019) (b) Population density (US Census Bureau, 2022)

In New Jersey, lead levels in Newark drew attention to the severity of this issue and culminated in the full replacement of LSLs in Newark. Other NJ cities, such as Trenton and Camden, where lead service lines were widely utilized, face comparable difficulties and are further behind in their LSL replacement efforts. In 2021, Governor Phil Murphy of NJ signed into law P.L.2021, Ch.183, which requires all community water systems to complete an LSL inventory by January 2022 and to replace all LSLs by 2031 (NJDEP 2023). In the meantime, it is difficult to identify when and where lead is being released in plumbing. The highest frequency require by law is every 6 months measured by inductively coupled mass spectrometry (ICP-MS), atomic absorption (AA), or anodic stripping voltammetry (ASV) (EPA 2010). Although non-laboratory endpoint monitoring techniques have been developed, potentiometric methods generally have short lifetimes, and colorimetric methods are often only single-use (Lin, Li, and Burns 2017). These all suffer from requiring an in-person sampling.

Figure 2 Inductively Coupled Plasma - Mass Spectrometer

The Sensor

To allow for long-term monitoring at multiple end-use points, researchers at the University of Michigan developed a low-cost platinum electrode sensor (Lin, Li, and Burns 2017). The sensor itself is about the size of a rice grain and costs less than 10 cents to produce at scale. Moreover, operation of this sensor requires only simple circuits and two AAA batteries. The small size and low-cost makes it ideal for end-use at multiple points. The inert material comprising the sensors allow for long-term use without degradation.

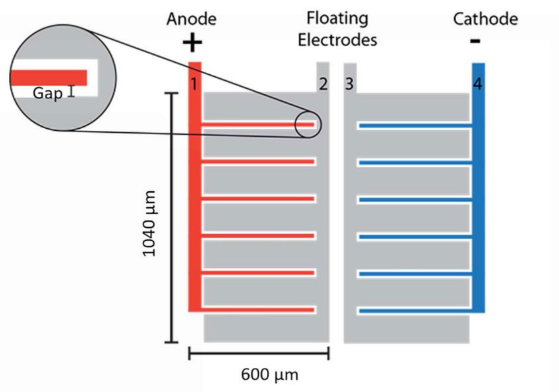

Figure 3 Diagram of interdigitated sensor (Nelson et al. 2022)

The mechanism behind the electrode sensor is to reduce and selectively precipitate metal cations from solution by applying a voltage through the electrodes, causing oxidation on one electrode (anode) and reduction on the other (cathode). These precipitates affect the conductivity between electrodes, allowing for detection of metal ions. The tendency is for lead ions to oxidize to PbO2 and precipitate on the anodes, and for the other common metal ions to reduce and precipitate on the cathode. Because PbO2 is the only oxidized compound precipitated on the anode that conducts electricity well, the resulting change in voltage may be used to detect the presence of lead in tap water (Nelson et al. 2022).

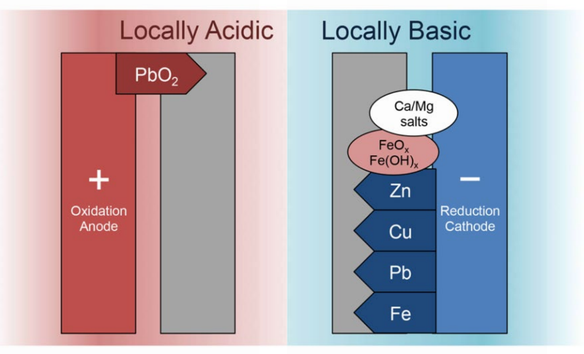

Figure 4 Operation of lead sensor (Lin, Li, and Burns, 2017)

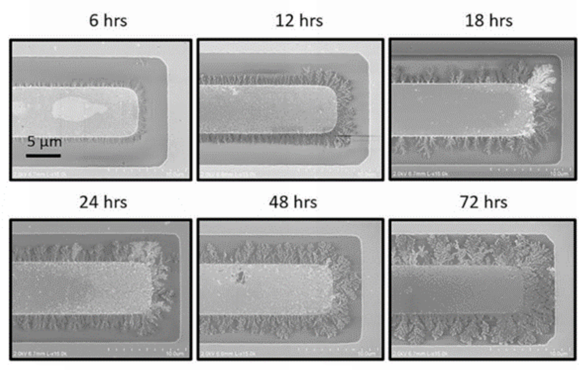

Figure 5 Precipitation of PbO_2 on sensor electrodes

Table 2. Resistivity of Reduced and Oxidized Metals and Drinking Water

oxidized metal	resistivity (Ω.m)	reduced metal	resistivity (Ω.m)
PbO_2	$2–74 \times 10^{-6}$	Pb	2.20×10^{-7}
ZnO	>2.2	Zn	5.90×10^{-8}
CuO	25–100	Cu	1.68×10^{-8}
Cu_2O	10^2 - 10^4		
$Fe(OH)_3/FeO(OH)/Fe(OH)_2/Fe_2O_3$	10^3 - 10^6	Fe	1.00×10^{-7}
drinking water	10–2000	—	—

Module Development

In order to collect data with the sensor, a module for controlling the voltage, recording data, and transmitting it for further processing is necessary. Michael has proposed using Arduino on the ESP32 microcontroller as a low-cost, WiFi enabled board that can be used for development of the module. We have been working on how to power the sensor and record data and use WiFi/Bluetooth to broadcast it to a computer,

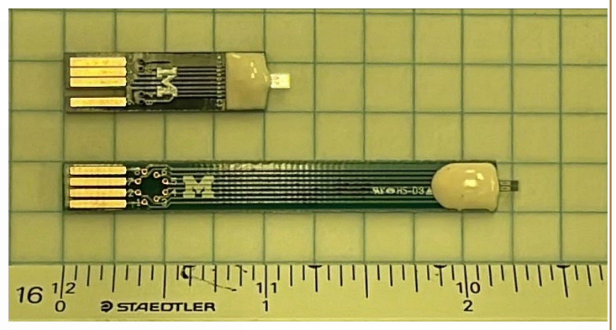

Figure 7 Sensor chips produced by the Burns Lab

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as well as how to monitor battery charge to ensure the voltage applied across the electrode is adequate. Michael developed code to flash the ESP32 to work with Arduino.

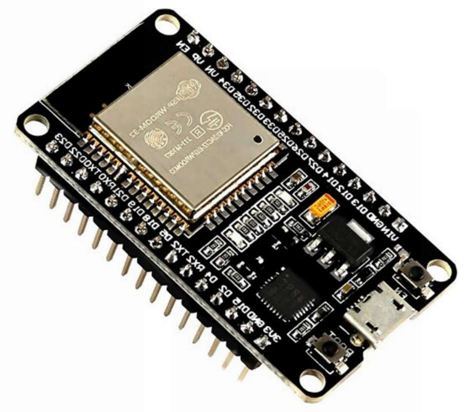


Figure 8 An ESP32 microcontroller

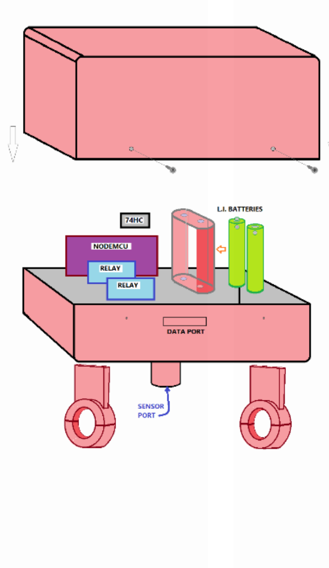


Figure 9 Module layout developed by Mr. Warholak's class at Bloomfield High School

At the same time, Michael, who volunteers as a robotics coach at Bloomfield High School (BHS) reached out to his former high school teacher, Michael Warholak, to mentor a team of high school students to develop a low-cost housing for the sensor module. Important features are that it will need to be water-tight to keep electronics from getting wet due to water leaks or humidity and that it needs to be relatively easy to install at a number of end-points. The current plan is to make a threaded connection in the housing so that it can connect between a faucet and the pipe connection to be as close to an end-point as possible.

Data Collection

The sensor has reached technology readiness level (TRL) 4 in that it has been tested and optimized against laboratory simulated water. The goal of this study is to increase the TRL to 6 by conducting studies in real systems with varying degrees of control. First, the system will be implemented on the pipe loop hosted at NJIT and using Newark's Pequannock water distribution system. Data such as phosphate, pH, chlorine, and Pb, Cu, and Fe concentration via ICP-MS will be routinely taken, making it a more controlled and well-characterized scenario. Options to include the sensor on pipe loops run by utilities, including the Passaic Valley Water Commission (PVWC) are ongoing, as these will provide a greater diversity of well-studied environments.

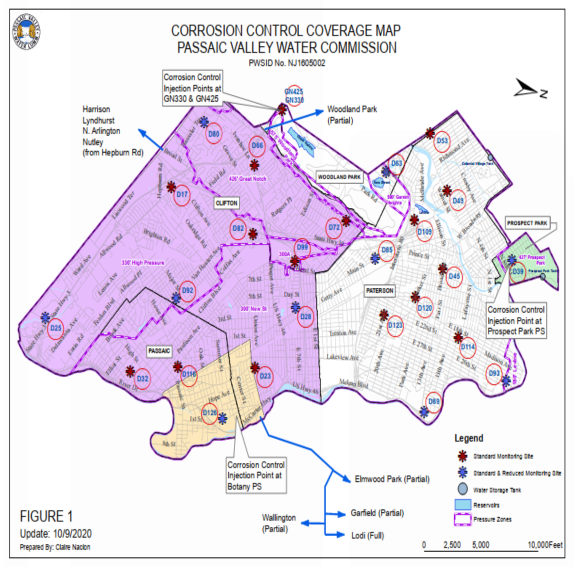
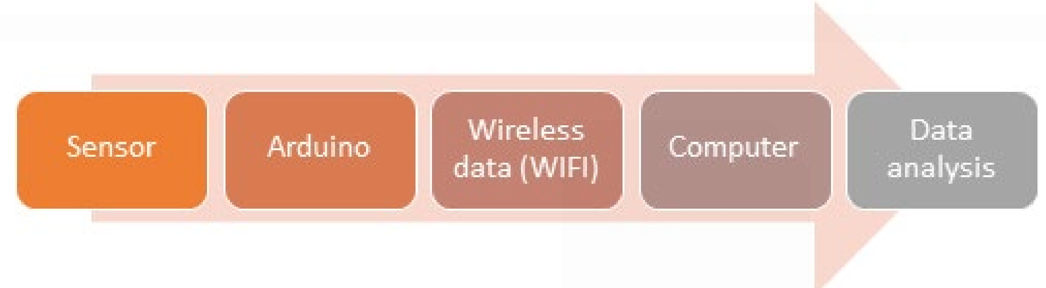


Figure 11 Map of PVWC Network Corrosion Control Locations

Figure 10 Pipe loop at NJIT using harvested lead-lined galvanized pipes.

In parallel, we are working with industry contacts to establish a collaboration to place the sensors on locations in water distribution systems where data are routinely collected and that are at or near endpoints. Our original partner was Newark Department of Water and Sewer Utilities, but they had finished their lead service line replacement by the time of the grant and were no longer interested in gathering data on lead in water. We were preparing to start a collaboration with PVWC, but they became short-staffed and were no longer able to pursue extracurricular research projects at the same level. We are exploring partnerships with American Water and Veolia.

Data Analysis



Once data are collected by the ESP32 modules, they will be stored and then collected using a WiFi enabled computer to capture the data locally. The data will then be uploaded into a database and the data will be analyzed for overall trends as well as their correlation with data such as phosphate, free chlorine, temperature, pH, conductivity, and flow.

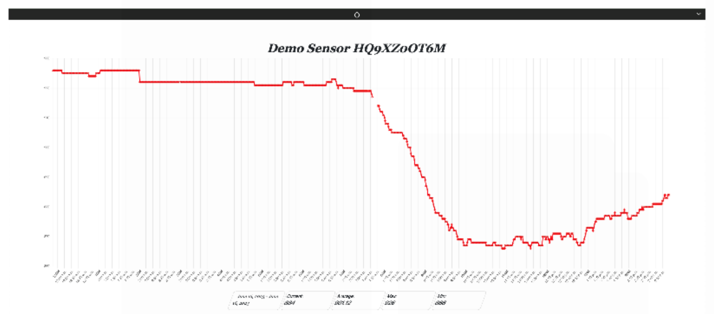


Figure 12 Website created by Michael Brzostek for displaying time series data

Machine learning techniques have shown promise in analyzing time series data. To improve the quality of the data, such techniques use feature extraction and preprocessing. Variable classification and concentration prediction can be made practicable by supervised learning techniques like neural networks and support vector machines. Unsupervised learning techniques, including clustering and anomaly detection, aid in pattern discovery and abnormality detection. Deep learning models, like recurrent neural networks, capture temporal dependencies for lead concentration forecasting and event prediction. Challenges include handling missing data, imbalanced datasets, and ensuring model interpretability. Future research should focus on developing interpretable models and addressing uncertainty in predictions. Applying machine learning in lead sensing can improve monitoring systems, enhance understanding of lead pollution, and contribute to public health and environmental sustainability.

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