

Cutting-Edge Lead and Copper Detection: A COMSOL and Deep Learning Synergy

ZUL KAZEEM

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Thesis Advisor: Prof. XYZ

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Cutting-Edge Lead and Copper Detection: A COMSOL and Deep Learning Synergy

Case Western Reserve University
Case School of Graduate Studies

We hereby approve the thesis¹ of

Zul Kazeem

for the degree of

Doctor of Philosophy

Prof. XYZ

Committee Chair, Advisor
Civil Engineering

Date

Pocapolise Eugene

Committee Member
Civil Engineering

Date

Demeter Insomnia

Committee Member
Civil Engineering

Date

Eucalyptus Koala

Committee Member
Civil Engineering

Date

¹We certify that written approval has been obtained for any proprietary material contained therein.

*Dedicated to Progress in
Civil and Environmental Engineering*

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Table 0.1. Symbol Definitions

ρ	Density
S	Strenght
F_v	Force
t	time
u	displacement

ABSTRACT

Cutting-Edge Lead and Copper Detection: A COMSOL and Deep Learning Synergy

Zul Kazeem

This article presents an innovative approach for detecting lead and copper in buried pipes by integrating COMSOL Multiphysics simulations with machine learning techniques. The enhanced model includes a soil block to replicate real-world conditions and utilizes accelerometers for data acquisition. The collected data is processed and analyzed using a convolutional neural network (CNN) to accurately identify the presence of these metals. This method aims to offer a more efficient and non-invasive solution to metal detection in water systems.

1 Introduction

1.1 Background

The detection of lead and copper in water systems is not only crucial for public health but has gained renewed urgency with the Environmental Protection Agency's mandate to replace all lead pipes within the next 10 years¹. Lead contamination, in particular, poses severe health risks, including developmental delays, neurological impairments, and cardiovascular issues, especially in children and pregnant women. Similarly, elevated levels of copper can cause gastrointestinal distress and other health complications. Traditionally, detecting these metals in buried pipes has relied on invasive methods such as physical excavation and chemical testing, which are labor-intensive, time-consuming, and disruptive to water supply systems. Moreover, these methods often require significant resources and may not provide real-time monitoring capabilities.

In response to these challenges, water authorities and researchers are actively exploring innovative, non-invasive detection methods that can accurately identify lead and copper pipes without the need for extensive excavation. This pursuit has led to advancements in simulation software and machine learning techniques, offering promising avenues for enhancing detection capabilities.

This study addresses these pressing needs by proposing a novel approach that integrates COMSOL Multiphysics simulations with machine learning algorithms. By combining the detailed environmental simulations provided by COMSOL with the analytical power of machine learning, this method aims to provide a robust and efficient solution for detecting lead and copper in buried pipes.

44 The integration of COMSOL simulations allows for the creation of realistic mod-
45 els that simulate the complex interactions between pipes, soil conditions, and
46 other environmental factors. This includes adding a soil block to replicate the con-
47 ditions in which pipes are buried, ensuring that the simulations closely mimic
48 real-world scenarios. Furthermore, the use of accelerometers for data acquisition
49 adds a layer of precision by capturing vibration and response data, which are criti-
50 cal indicators for detecting the presence of metals based on their distinct physical
51 properties.

52 In parallel, machine learning techniques, particularly convolutional neural net-
53 works (CNNs), are employed to analyze the collected data and distinguish between
54 lead and copper pipes. By training the CNN with a large dataset generated from
55 COMSOL simulations, this study aims to enhance the accuracy and reliability of
56 metal detection, thereby offering water authorities a practical tool for identifying
57 and prioritizing pipe replacements.

58 **1.2 Motivation**

59 Lead and copper contamination in drinking water is a significant public health con-
60 cern¹. Traditional detection methods involve physical inspections and chemical
61 tests, which can be both time-consuming and disruptive. Recent advancements
62 in simulation software and machine learning offer potential solutions to these
63 challenges by providing non-invasive, accurate, and efficient detection methods.

64 Overall, this integrated approach not only addresses the immediate need for
65 efficient metal detection in water systems but also sets the stage for future advance-
66 ments in real-time monitoring and predictive maintenance strategies. As water
67 utilities strive to comply with regulatory mandates and safeguard public health, in-
68 novative solutions that blend simulation technologies with advanced analytics are
69 poised to play a pivotal role in transforming how lead and copper contamination
70 are managed in infrastructure systems.

71 2 Literature Review

72 Numerous studies have explored various methods for detecting lead and copper
73 in water systems. Traditional methods include physical inspections and chemical
74 testing, which have limitations in terms of cost and efficiency. Recent research
75 has not focused on the use of simulation software, such as COMSOL Multiphysics,
76 and machine learning algorithms to enhance detection capabilities. This is thus
77 an integrating these technologies for practical applications remains an area of
78 active research. The following article is structured as thus: the methodology that
79 describes the process that was used for the experiment, the result that shows the
80 output from the model, the discussion, and finally the conclusion.

81 3 Methods

82 3.1 Computational Methods

83 3.1.1 Model

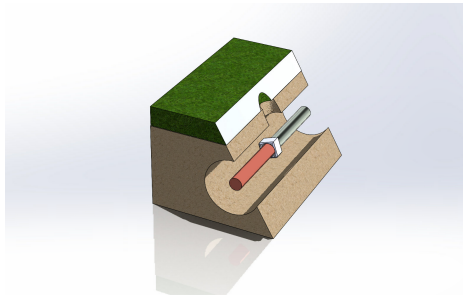
84 The simulation model consists of a soil block with uniform properties to replicate
85 real-world conditions as much as possible but also to the extent that the model
86 can allow. Steel was chosen as the material for the rod to be used with a hydraulic
87 jack of 1000KN to ensure effective load transmission to the pipe.

88 The model is built using COMSOL Multiphysics using the solid mechanic model
89 to simulate the effect of load on the pipe. The enhanced model was imported into
90 Matlab, where random values were assigned to the pipe and load properties to sim-
91 ulate various scenarios. This step was essential for generating a comprehensive
92 dataset.

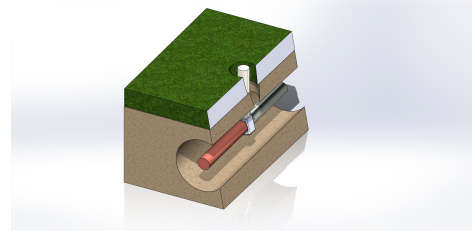
93 3.1.2 Dataset Generation

94 Approximately 5000 datasets were generated to train the machine learning model.
95 The large dataset is critical for improving the accuracy and reliability of the CNN
96 used for detection.

$$\rho \left(\frac{\partial^2 u}{\partial t^2} \right) = \nabla \cdot \mathbf{S} + \mathbf{F}_v \quad (3.1)$$

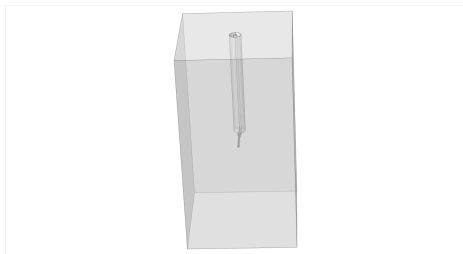


(a) Section of the buried Copper and Lead Pipe

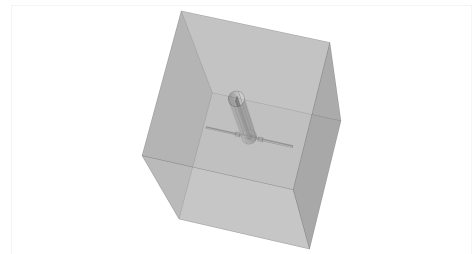


(b) Section of the buried Copper and Lead Pipe with steel rod

Figure 3.1. Section of the buried Copper and Lead Pipe with steel rod



(a) Side View



(b) Top View

Figure 3.2. Side and Top View of the Solid

97 **Data Categorization.** The generated data was separated into two categories: lead
 98 and copper. This categorization enabled the CNN to learn the distinct characteris-
 99 tics of each metal.

100 **Model Training.** The categorized data was used to train the CNN, aiming to develop
 101 a robust detection system capable of identifying the presence of lead and copper
 102 in buried pipes.

103 4 Results

104 4.1 Computational Results

105 The integration of COMSOL simulations with machine learning resulted in a com-
106 prehensive dataset representing various real-world scenarios. The CNN was trained
107 with this data, showing promising accuracy in distinguishing between lead and
108 copper based on the recorded acceleration readings.

Description	Point graph
X	Height
0	5.817362260551916E-20
1	5.817362260551916E-20
2	6.046114033737459E-20
3	5.076492751732623E-20
4	2.0101101950650483E-20
5	6.082783728329581E-20
6	6.082783728329581E-20
7	6.082783728329579E-20
8	1.3190892577783899E-20
9	4.7556868646350063E-20
10	4.755686864635008E-20
11	4.7556868646350033E-20

Table 4.1. Result of Lead and Copper after Sinusoidal load has been applied.

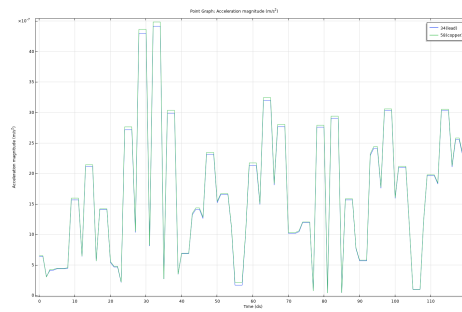


Figure 4.1. The graph that distinguishes between lead and copper.

109 5 Discussion

110 The combined use of COMSOL and machine learning demonstrated significant
111 potential in improving the efficiency and accuracy of metal detection in water
112 systems. The enhanced model, which includes a soil block and steel rod, effectively
113 simulates real-world conditions. The generated dataset and subsequent training of
114 the CNN highlight the feasibility of this approach. However, the process was slowed
115 by the computational resources required, indicating a need for optimization in
116 future work.

117 6 Conclusions

118 This study presents a novel method for detecting lead and copper in buried pipes
119 by integrating COMSOL simulations with machine learning techniques. The en-
120 hanced model and extensive dataset generation contribute to a more accurate
121 and efficient detection system. This is not only limited to lead and copper de-
122 tection but can be expanded for uses in other areas that involve detection of metal
123 underground without digging into it.

124 7 Future Research

125 Extensive field testing and validation in various environments would be crucial
126 to ensure the model's robustness and accuracy in real-world conditions. Collabora-
127 tions with environmental agencies or institutions for large-scale validation studies
128 could provide valuable insights and further enhance the model's reliability.

References

- 130 [1] EPA. Lead and Copper Rule, November 2023. URL [https://www.epa.gov/](https://www.epa.gov/dwreginfo/lead-and-copper-rule)
131 [dwreginfo/lead-and-copper-rule](https://www.epa.gov/dwreginfo/lead-and-copper-rule).