

**SCHOOL OF MINES AND ENGINEERING**

**LEVERAGING HYBRID SYSTEMS (INTERNET OF THINGS AND OPTICAL FIBER), TWO-WAY COMMUNICATION SYSTEMS AND MACHINE LEARNING MODELS TO IMPROVE SAFETY AND COMMUNICATION IN UNDERGROUND MINES**

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**A PROPOSAL SUBMITTED IN PARTIAL FULFILMENT FOR THE DEGREE OF MASTER OF SCIENCE IN MINING ENGINEERING IN THE DEPARTMENT OF MINING AND MINERAL PROCESSING ENGINEERING OF TAITA TAVETA UNIVERSITY**

**JANUARY 2025**

# Declaration

**This proposal is my original work and has yet to be presented for a degree at any other university.**

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# Abstract

Underground mining has posed significant health and safety challenges to underground mines. These include accumulating toxic and hazardous gases, poor air quality, exposure to particulate matter, extreme temperature and humidity, and a poor communication system. Over the past, underground miners, mainly artisanal and small-scale miners, have used traditional methods to monitor the above challenges and communicate with the underground miners and the support staff on the mine's surface in times of emergence. This has been done through manual checks such as human senses, outdated wired systems, and human movements from outdated wired systems underground to the surface to pass information. However, these methods have failed because they are unreliable and inconvenient during emergencies; instead, they further endanger the underground miners' safety by exposing them to respiratory illness and black lung diseases and also delayed communication during emergencies, which increases the number of fatalities and injuries to the underground miners.

This research will address these problems by developing an innovative hybrid monitoring system and a two-way communication system for underground miners. This will be achieved by integrating Internet of Things technologies and machine learning models. The proposed innovative system will utilize sensors such as MQ135, MQ7, DHT11, and SDS011, a microcontroller, Zigbee modules, Raspberry Pi4, and a media converter to monitor the underground mine parameters like the gas concentrations, temperature and humidity, and particulate matter. The proposed system will collect the data from the underground environment, process the near real-time data, and give an immediate response based on the thresholds of the analyzed parameter. The system will also use the machine learning model to carry out predictive measures to help the experts in planning.

Data collected from various sensors in the underground mines will be processed in near real-time. Depending on the threshold analysis, an alarm will be triggered for immediate response. The two-way emergency communication will be used to give immediate instructions to the underground miners. This innovative approach demonstrates how emerging technologies can transform the mining industry. This research paper will showcase the importance of leveraging the Internet of Things and Machine Learning models to improve underground air quality predictions and safety, especially for artisanal and small-scale miners.

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# CHAPTER ONE: INTRODUCTION

## 1.0 Background Information

Underground mining is the extraction of valuable minerals such as gold, diamond, and tsavorite beneath the earth's surface to lower the cost of extraction, whereas surface mining is not viable. Due to global economic growth, the constant demand for these valuable minerals has fueled the extractions to ~~dig deeper~~ deeper levels. As the underground miners extracted minerals more profoundly, the working conditions in the mines became harsher and more confined. This has intensified health and fatal challenges to underground miners due to the accumulation of toxic gases, poor air quality, and extreme environmental challenges like fluctuating temperature and humidity(Liu et al., 2024; Wagner, 2019) .

In the United States, underground mining has recorded several fatality rates. For instance, from the 1990s to 2007, approximately 1601 cases of mine fires were reported. In Punja, Pakistan, it was reported by the Directory of Mines that a higher number of roughly 38% of underground mine accidents were due to gas accumulations. ~~It is estimated that the~~ Blasting involves releasing carbon dioxide or methane gases, which account for approximately 33.8% of the casualties in the underground mines. Even though the methane gas released from the underground mines has a flammable range of roughly 5-15%, a low amount of the methane gas can result in serious harm to the underground miners(Matloob et al., 2024).

In Africa, underground mining has also contributed to health and fatal issues. For instance, South Africa reported over 300 coal mine explosions, with over 600 mine injuries and over 1037 deaths in the period from 1981 to 2007. In addition, Anglo-Gold Ashanti Mine Company in 2011 recorded a case of death of an underground miner. The employee's records indicated that the worker contracted chronic obstructive airways and tuberculosis due to exposure to the mine's dust(Raheem, 2011).

In East Africa, especially Kenya, there is limited published evidence on the statistics of underground mines' health and fatal issues. However, like other mines, ~~U~~underground mines in Kenya are exposed to underground challenges, such as poor air quality, accumulation of toxic gases, and temperature and humidity fluctuations. Accumulating toxic gases differs from mine to mine based on geological conditions and the type of explosives used. For instance, gold miners commonly suffer from silicosis, a disease caused by inhalation of silica dust from quartz. The effects of the inhalation of silica dust can be felt after 5-10 years of heavy exposure. After 5-10 years, the affected miners may develop difficulties in breathing, which may lead to death (Ogola et al., 2002).

The rapid growth of technology has provided solutions to the above problems experienced by underground miners. This has been achieved by implementing the Internet of Things and machine learning. The Internet of Things concept has been used to monitor the underground working environment. For instance, Shangwan Coal Mine, Erdos, in China, has implemented a robust, innovative system by upgrading its previously developed cable environmental monitoring system to a wireless sensor node. This system includes environmental monitoring and can carry out periodic inspections and interruptions. Machine learning models have been used to take inputs to train various models that produce a desirable outcome(Kim et al., 2020; Morgenroth et al., 2019; Zhang et al., 2014) .

This research focuses on developing a hybrid underground monitoring system in the mining sector. The research will address common problems underground miners face, such as fluctuating environmental conditions, poor air quality, and the limited visibility of near real-time data on the accumulated toxic and hazardous particles. These problems are due to gases and fumes released through blasting and heavy machines such as drilling machines such as carbon monoxide, carbon dioxide, and particulate matter (Parra, 2021). The current traditional system used to monitor the underground mines heavily relies on manual checks or fully wired setup systems, which need to be more sustainable and reliable. The proposed system will integrate MQ7, MQ135, DHT11, and SDS001 sensors, a microcontroller (Arduino Uno) Zigbee modules, a media converter, optical fiber, Raspberry Pi4, and a machine learning model to monitor, report, and predict near real-time underground environment parameters such as particulate matter, gas concentrations, temperature, and humidity The system will also use IP phones and switches to enhance a two-way emergency communication system that will enhance the communication system. Leveraging IoT, two-way communication systems, and machine learning solutions, the project will improve underground safety protocols, lower operational protocols, and enhance near real-time monitoring systems.

The successful execution of this research proposal will rely on the practical implementation of the Internet of Things through data collection from different sensors and the transfer of the data from the sensors to the base stations via the Xbee modules. The Raspberry Pi4 will analyze the data and give an immediate response to the local miners. The base station data will be further predicted through machine learning algorithms, and the information will be available to the expert for further planning.

The importance of this project to industrial practice and knowledge advancement is that the system will demonstrate how IoT technologies such as sensors, Arduino, Zigbee modules, and Raspberry Pi can be innovatively applied to the real world to solve various problems in the mining sector. This will set a precedent for further integrating technologies in the mining industry. The project will also help multiple mining companies comply with environmental compliance standards by accurately monitoring PM 10 and PM 2.5 particles. This will lower the ecological impact. Finally, the system will help collect near real-time information to ensure immediate response to toxic and hazardous conditions, safeguarding miners' health and lives. The application of machine learning will inform experts on the proper planning and strategies for managing the underground environment. The outcome of this project may revolutionize artisanal and small-scale mining practices by developing more innovative, safer, and more efficient operational frameworks for underground miners.

## 1.2 Problem Statement

Underground mining, mainly artisanal and small-scale miners (ASM), experiences critical challenges related to health and safety. This is because underground miners from the ASM are usually exposed to toxic and hazardous gases, fluctuating temperature and humidity, and particulate matter from blasting, drilling, and machines used in underground mines. However, these artisanal and small-scale miners operate outside the formal safety frameworks, especially from Kenya. They usually rely on sensory detections, such as smell, touch, and vision, to identify these hazardous and toxic gases and particulate matter levels. The methods used by these miners are unreliable and highly expose them to chronic health risks such as respiratory illness and black lung diseases, which are caused by prolonged exposure to carbon monoxide, carbon dioxide, PM2.5, and PM10 particles.

The lack of near real-time data monitoring and the need for advanced adoption of predictive analytics in underground mines to forecast hazardous conditions has exacerbated the risks. For instance, when the accumulations of toxic and hazardous gases have exceeded the safety thresholds, the absence of prompt and accurate alerts to underground miners can result in professional injuries and fatalities. However, the lack of machine learning models in the underground mines has limited the ability to analyze the historical data for various patterns, predict environmental challenges in the underground mines, and implement proactive safety measures. The gap in machine learning technology has prevented effective management of the underground environment and exposed various miners to preventable health risks. This research thesis will address poor underground monitoring systems and machine learning predictions of the underground environment by leveraging IoT and machine learning technologies.

## 1.3 Research Justification

Mine safety and enhanced communication in underground mines should be prioritized. These issues may be addressed using emerging technologies, including the Internet of Things (IoT), artificial intelligence (AI), and Machine Learning (ML). These technologies may become handy in monitoring near real-time and predicting the mine environment, such as air quality in underground mines. The challenges experienced in the underground mines include inhaling toxic gases such as carbon monoxide, carbon dioxide, and particulate matter from the blasting, geological strata during drilling, and heavy machines. Traditionally, miners used canary cages to monitor safety, ~~whereas~~ where sensitive birds were utilized to detect the levels of carbon monoxide. With the loss of biodiversity, this method may not hold, and thus, the mine workers would be exposed to these gases, causing fatality. Another attempt has been using flame safety lamps that extinguish the flame before the gas levels reach dangerous levels. This ~~suitable~~ method might not be very effective in detecting trim levels of gases and does not offer communication services to the miners on the surface of the mines for effective operation. Furthermore, the emerging technologies that may help improve communication networks in underground mines will significantly benefit the artisanal and small-scale miners because increased productivity leads to economic growth, resulting in improved livelihoods in line with UN Sustainable Development Goal (SDG) #3. Improving the air quality monitoring in underground mines and providing rapid communication will help address the underground mine workers' health and safety concerns and lower the fatalities in line with SDG #8. By enhancing underground communications, increasing productivity, and reducing underground accidents, this research will promote decent working conditions and develop sustainable economic growth for the miners, thus promoting SDG #9. The projects also help achieve the African Union Agenda 2063: Aspiration 1: prosperous Africa through increased productivity and economic growth.

## 1.4 Objectives

### 1.4.1 Main Objective

The main objective of this research proposal is to utilize the Internet of Things (IoT) and machine learning to enhance safety and communications in underground mines.

### 1.4.2 Specific objectives

The specific objectives are to:

1. Design an Internet of Things (IoT) sensor network monitoring system with an emergency response system for underground mines.
2. Integrate a machine learning model to improve the emergency response system and predict the conditions of the underground mines.
3. Develop a two-way communication system to enhance effective communication during an emergency.

## Scope of Study

The scope of the study is limited to the underground mining industry, which will use the technology to monitor CO2, CO temperature, humidity, PM2.5, and PM10. The system will enhance communication and provide an emergency response to the miners. This study might not explore all the potential Internet of Things technologies or address all the safety and communication challenges in underground gemstone mines. Financial and other resource constraints may limit the duration and scale of this research proposal. The study will also focus on the geological aspect of gemstone mining and broader social and economic issues.

# CHAPTER TWO: LITERATURE REVIEW

## Overview

This chapter comprehensively reviews the existing literature on the history of underground mine detections, the Internet of Things, machine learning algorithms, and their application in underground mining.

## 2.1 Introduction

Mining is the economic extraction of valuable minerals or other geological resources from the earth's surface. The valuable minerals can be from the ore body, veins, lodes, seams, placer deposits, or reefs. The mine's life cycle starts with exploration, development, production and ends with closure and post-mining land use. There are two types of mining: surface or open-pit mining and underground mining. Surface mining is the oldest method~~; its~~ where minerals are extracted through open pits. This is usually achieved by removing a significant amount of overburden. These overburdens are a mixture of soil and rocks that cover the ore deposits. The method involves mechanical excavations like the open pits and open casts such as strip mining. The thin deposits in this method are mined in a series of benches, while thin deposits are mined in single benches. In underground mining, ore bodies are in the buried ~~deposits~~. The deposits are accessed through constructed shafts or tunnels. This method of mining provides minimal waste as compared to surface mining (Balasubramanian & Balasubramanian, 2016). However, underground mining is accompanied by many health and safety challenges due to harsh and confined working environments. Some of the challenges experienced are an accumulation of toxic gases, rock bursts, and extreme temperature and humidity. Therefore, introducing technology to these stages will play an important role in improving health issues in the underground mines.

## 2.2 The History of The Underground Mines Gas Detections

The dangerous underground mine conditions, especially the accumulation of dangerous gases such as carbon monoxide, carbon dioxide, hydrogen sulfide, and methane in the underground mines, led experts to seek techniques for early detection. Before the establishment of advanced sensor technology, various techniques were used, such as canary birds, flame light, a human wick with a wet blanket, and warm-blooded animals (Pollock, 2016). Some of these techniques were more reliable than other methods. For instance, in the 20th century, underground miners in the coal industry used the canary bird as a sentinel animal to detect carbon monoxide. Underground miners realized that canary birds exhibited more visible and pronounced reactions to carbon monoxide than other animals like mice. Because of their highly efficient respiratory systems and small size, these birds succumb more rapidly than humans when exposed to carbon monoxide. It is estimated that the bird would collapse 20 minutes before underground miners exhibited any symptoms. When miners observed any signs of distress in the birds, like fainting or falling from their perch, the underground miners would evacuate the mines with immediate effects. Using other animals like mice was challenging because identifying signs of distress, such as crouching or squinting and pinkness in the snout, was challenging to detect in dim lights in the underground mines (Leech, 2024).

Their sensitivity, cost-effectiveness, and availability bolstered the popularity of using these birds to detect carbon monoxide. The bird breeders and the pet shops supplied the canaries to the mining companies. These companies purchased imperfect birds that rendered them unfit for sale as pets. Even though the reliance on the canary birds looked rudimentary compared to modern sensor technologies, this outlined the resourcefulness and ingenuity of the underground miners in confronting their professional perils. Therefore, the canary image in the underground mines has transcended its lateral meaning and become a metaphor for warning the early gas detections of the impending danger in the underground mines (Leech, 2024; Pollock, 2016). Phasing out of the canary birds in the late 20th century for more sophisticated gas detection technology marked an essential advancement in the mine's safety. This underscored the continuous effort to protect the well-being of the underground miners. Modern sensors can detect the accumulation of toxic and hazardous gases in much smaller quantities than animals. Using canaries, the underground miners are a powerful symbol that underground miners experience health and safety issues, and ingenuity is employed to mitigate the challenges they encounter.

## 2.3 History of the Internet of Things

The Internet of Things is defined as the network of virtual and physical devices capable of collecting various data in the surrounding environment and exchanging the collected data between the devices or through the Internet. Multiple devices are embedded with sensors, electronics, and software for data collection. The data exchange is then achieved by connecting the devices to the internet or local area network (Sembroiz et al., 2018). This technology is considered the third wave of the internet. Its history began in 1892 when a coke mineral bending machine was connected to the internet. The system was set to display the bottle quantity and the mineral temperature in the machine (Yalli et al., 2024). Later, the concept of ubiquitous computing was introduced in 1991 by Mark Weiser. Mark aimed for technologies to function on human perceptions periphery (Gray, 2024). In 1999, IoT was coined by Kevin Ashton, the executive director and co-founder of the Auto-ID Centre at Massachusetts Institute of Technology. In 2008, the first IoT conference was organized and held. Thereafter, several countries embraced the idea of IoT and drafted an action plan. In 2009, countries like Belgium released their action plan in Brussels. In 2010, China published its 12-year development plan in 2014. There has been skepticism about embracing the IoT in the last decades until big companies like Samsung, Apple IOS, Google, and Gear Net Labs used the technology for significant business opportunities. Cisco has revealed that the Internet of Things has a possible financial value of approximately $14 trillion. Their reports stated that more than 25 billion devices were connected before 2020. It was projected that in 2023, more than 29.4 billion devices would be connected. However, Intel projects that by 2025, the Internet of Things may reach approximately $ 6.2 trillion in market value. Sensor productions will increase globally, especially in retail, to 20%, industrial, to 25%, automotive to 31%, power and utilities to 32%, and mining and energy areas to about 33% (Yalli et al., 2024).

The strength of the above research is that it showcases comprehensive technological advancements. Their research has shown significant progress in the Internet of Things, data processing, enhanced connectivity, and application development. Their research has acknowledged the criticality of security in the Internet of Things. Their research shows that despite technological advancements, the current technology needs a standardized architecture that hampers the scalability and interoperability in large-scale deployment. This justifies the need for further development of the standardized architecture, which incorporates scalable and interoperable frameworks for the diverse Internet of Things technologies and their applications.

## 2.4 Application of The Internet of Things In Underground Mining

The emergence of the Internet of Things technology has transformed both surface and underground mining. The Internet of Things has enabled seamless data flow from underground mines to base stations through wireless systems that connect various sensors, devices, and machinery. Underground mining connections pose a unique challenge in connectivity compared to open-pit mining. Wireless network systems such as Bluetooth (IEEE802.15), WiFi (IEEE802.11), and WiMAX have been widely used to enhance communications. However, the emergence of new technology, such as ZigBee, which is guided by the Ultra-Wide Band (IEEE 802.15.4), provides innovative solutions (Pramanik et al., 2024). The Internet of Things has been used for environmental monitoring in underground mining. This technology has enabled the deployment of sensor networks to collect near real-time data on temperature, humidity, and air quality, and it detects harmful gases such as carbon monoxide.

The technology has used Bluetooth and ZigBee to ensure a safer underground working environment. IoT technology also uses RFID (Radio Frequency Identification) to provide real-time tracking of the local workers. An active RFID device has performed the passive devices as they can extend the communication range to over 100 meters in the open areas compared to the limited 5-10 meters of the passive tags. A global system for mobile communications networks is used to enable efficient communication between underground miners and base station operators. This technology can also automate underground operations and improve operational efficiency. This involves equipment monitoring and control. IoT enables remote monitoring and control of underground mining equipment. This results in real-time performance data. The technology helps collect data on fuel consumption, equipment operation, and maintenance feedback. This data is essential for predictive maintenance and optimizing the performance of the equipment. This technology has also been used to monitor vibrations from blasting and moving vehicles (Pramanik et al., 2024).

The strength of this research is that it has demonstrated the effectiveness and feasibility of utilizing wireless sensor nodes to collect real-time data that helps in the early detection of mining hazards and location monitoring and tracing of the personnel. For instance, the Intelligence System at Shangwan Coal Mine has described an advanced wireless sensor node that enhances the previous cable-based monitoring system. The advanced coal mine system can detect fire bursts in their early stages and pinpoint the fire's location inside the mine. The system is also capable of real-time location tracking of the underground miners and, hence, safety measures by tracking the proximity of the underground miners to the hazardous areas or equipment. The weakness of this study is that the research focuses on limited deployments or specific applications. This enables further research on the scalability and reliability of the system to enable reliable data transmission and effective communication of the modules across complex underground mines. The other weakness of the research is that the system lacks accuracy and reliability in the challenging environment because the signal propagation in the underground mines is usually unpredictable due to the obstacles, dynamic conditions, and multipath. Battery life and power consumption are also significant challenges experienced when maintaining the system because of energy-intensive technologies, such as the UWB, which strains the battery's life and requires frequent charging. The lack of standardization for the IoT architectures and the communication protocols has also made the interoperability and integration of the system challenging. Even though this source offers a proper foundation for understanding the possible Internet of Things in Underground mining, there are various gaps in the development of the standardized Internet of Things architecture, addressing the communication challenges in the harsh underground environment, enhancing energy harvesting techniques, and finally strengthening data security and privacy.

## 2.5 The Role of Machine Learning in Underground Mines

Machine learning has become an essential technology in the mining sector, especially in the challenging and complex domain of underground mine planning. These technologies' ability to provide predictive insights, process big data, and identify patterns has made them a significant tool for enhancing safety, improving resource recovery, and optimizing operations. In underground mining, machine learning models have been used to optimize drilling and blasting performance. The model has been used to predict various algorithms that have helped fine-tune drilling and blasting parameters (Ghojoghi et al., 2024). This has maximized efficiency and lowered operational costs. Machine learning models have also been used to predict ventilation resistance (Cao et al., 2024; Semin & Kormshchikov, 2024). This has enabled the optimization of the mine's ventilation systems, hence improving the mine's safety and energy efficiency. The model has also been used to simulate underground fires where the technology has offered invaluable tools for training and developing risk mitigation strategies inside the mine's ventilation circuits (Gu et al., 2024). The model has also been used to predict geotechnical risks such as seismic events and rock bursts, safeguarding the infrastructure and underground personnel (Cai, 2024; Wojtecki et al., 2022). ML has also been used to indicate mining dilution, where the ore and waste rock are mixed (Yu et al., 2021a). This has helped maintain the ore quality and optimize the production schedules. Finally, the ML was also used to carry out ore grade estimation. The advanced machine learning algorithm can assess ore grade variability in the ore body (Abbaszadeh et al., 2021; Tsae et al., 2023; Yu et al., 2021b). This has helped optimize the extraction sequences and minimize resource recovery.Even though there have been advancements in machine learning models, their applications to underground mines have experienced various challenges. For instance, most of the current implementations in machine learning are siloed. This means the models focus on specific tasks without integrating with other models. This approach has limited the ability to achieve comprehensive mine planning and optimization of the production schedule. Moreover, when this model technology improves individual predictions, the siloed fragmented approach usually lacks direct connections to the overarching production schedules. This leaves a gap in translating technological benefits into practical outcomes. The other challenge is that it relies on the accuracy and currency of the data used in the mathematical models for production scheduling. The machine learning model relies on static datasets, sometimes outdated as mining conditions evolve. This results in discrepancies between the actual production performance and the forecasted schedules. To address these challenges, it is essential to unlock the full potential of machine learning in underground mining.

This research can be necessary because it will help unlock the full potential of machine learning in predicting the underground environment. This learning is also essential to focus on integrating the machine learning subsystems that will enable the development of synergistic connections between the models. This will allow individual applications to contribute more effectively to optimizing IoT systems. The creation of the dynamic data updating mechanism will also be important because this will enable the model to be fed with the current data on the evolving underground mining conditions. Developing the function-specific surrogate model and the centralized data repository is also essential for prediction and thorough analysis.

## 2.6 Emergency response system

The development and innovation of new technologies have enhanced the design and implementation of a safety-pro-monitoring system that can identify possible risks and respond quickly to issues. The system comprises a computer integrated with software containing a Mine Warning Index. The Mine Warning Index is a quick and easy assessment of the mine states as a single index (Jo & Khan, 2017). The Mine Warning Index provides a platform to monitor the state of the underground mines to see if it is normal or abnormal. The index depends on the threshold limits values of the underground gas concentrations, temperature, and humidity. The threshold limits depend on the exposure limits that represent the concentrations of the airborne individual chemical substance, which should neither impair the health of the underground miners nor cause undue discomfort, according to the current knowledge of nearly all the workers.  In addition, the exposure limits guard against the irritations or the narcosis that precipitates industrial accidents. Time-weighted average (TWA) is the exposure limits of underground workers to airborne contaminants over 8 hours per workday. During the average period of 8 hours, the exposure of the TWA limits is permitted, providing that the equivalent excursions below the limits for the working day compensate for the excursions. Extractions exceeding the TWA concentrations should be restricted because some substances give rise to acute health effects despite brief exposure to high concentrations. Short-term exposures STELs are expressed as the airborne concentrations averaged for up to 15 minutes. Underground miners should not be exposed to this condition continuously for more than 15 minutes or more than 4 times per working day (Jo & Khan, 2017). The ceiling some gases have a TLV with a maximum limit that can never be surpassed because they are hazardous.

# 3. METHODOLOGY

## Introduction

Chapter three of this research will define the research methods and the logical steps of achieving the research methods. The primary research method of this project will be conducting a study, literature review, and conceptual modelling. After understanding the structured approach of the system, the steps will be:

## 3.1 Designing an Internet of Things (IoT) Sensor Network Monitoring System With an Emergency Response System For Underground Mines

The study will examine the technological research gap and how the technology can be successfully implemented for artisanal and small-scale miners. The study will use wireless technology to transfer data from the underground mines to the base station. This will be achieved using modern sensors such as MQ7, MQ135, DHT11, and SDS001 sensors to measure the standard underground environmental parameters that affect the underground miners. The data will then be processed locally with Arduino Uno's microcontroller and transferred to the base station through the ZigBee modules. The data will then be processed on Raspberry Pi4. Raspberry Pi4 will act as the system's local server. Based on the understanding, a modern IoT system will be designed and developed using an app eraser ia. A virtual prototype of the Internet of Things system will be designed to simulate the performance and the data transmissions from the underground to the base station. An experimental setup of a physical prototype will be developed to validate the sensor performance in actual and simulated underground mine conditions. The miners will then be trained on how to use the technology. Data will be collected for further analysis. An alarm system with LED lights will give feedback to the underground miners. A survey will gather the underground miners' views on the technology's reliability, accuracy, and constraints.

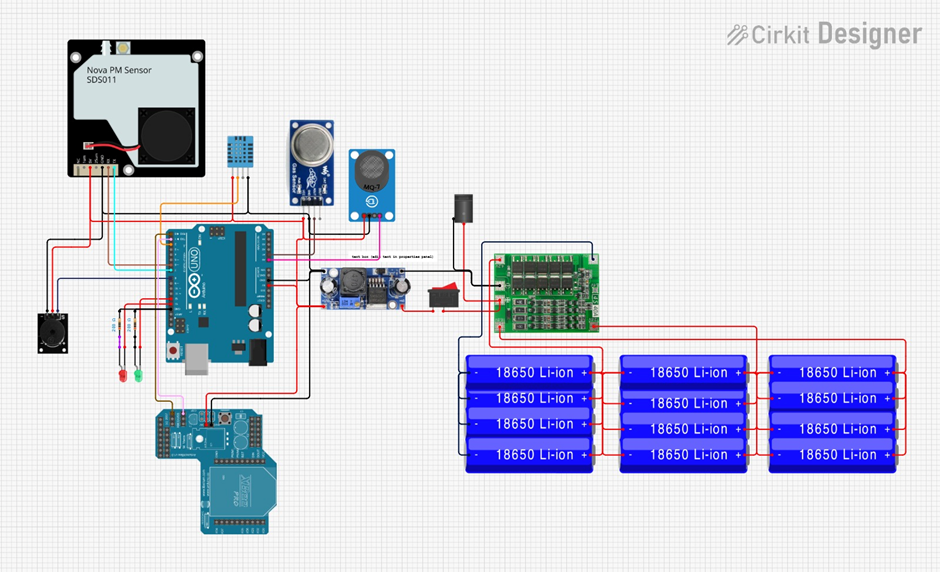


Figure : Sensor Node placed at the production area

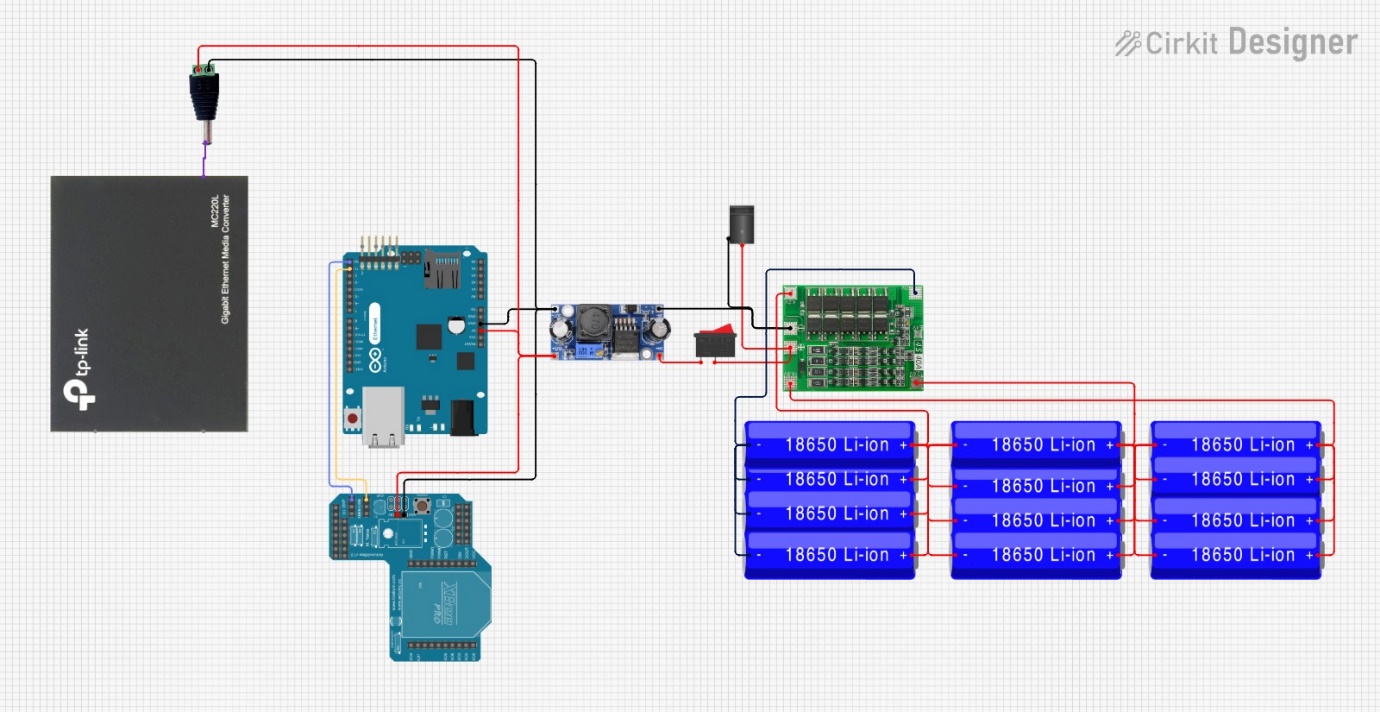


Figure : Router Node placed at the Underground Base Station

## 3.2 Integrating Machine Learning Model To Improve Emergency Response System And Predict The Underground Mine Conditions

The second step will be integrating machine learning models to evaluate the data parameters and provide an innovative emergency response system that will notify the underground miners about the situation. A ruled-based algorithm will analyze the stored data and trigger the alarms and LED lights for the predefined thresholds. The integrated emergency protocols will be simulated using machine learning models and decision trees. The integrated response system will be tested in underground mining conditions. A survey will be conducted to collect feedback from the underground miners on how the system is effective. This will be important for refining the system further. The system will use mine environment index thresholds to identify gas accumulations, particulate matter, temperature, and humidity. Machine learning algorithms will predict and project underground conditions for future planning. Google Calob will be the environment used to train the machine to predict underground data. Based on the model, a suitable machine-learning algorithm will be chosen for time-series predictions or regression tasks. The recorded dataset will be split into training, validation, and test data, e.g. (70-20-10) %. The model will be trained using three weeks of historical data and validated using the unseen data. The evaluation performance of the model will be done using metrics such as the Mean Absolute Error, Root Mean Square Error, and R-squared. Hyperparameter tuning will be performed to optimize the model.

## 3.3 Develop A Two-Way Emergency System To Enhance The Communication System During An Emergency.

The designed system will focus on creating a robust architecture that enables communication between the underground miners and the support staff on the underground surface. A communication network diagram will visualize the connections between the IP phone switches and Raspberry Pi, ensuring system configuration and layout clarity. Raspberry Pi will serve as an auxiliary Dynamic Host Configuration Protocols server that will dynamically allocate the IP address and work as the central server for communications.

# CHAPTER FOUR: EXPECTED RESULTS, WORK PLAN AND BUDGET

## 4.1 Expected Results

The expected results at the end of this research are as outlined in Table 3.

### Table 3: Expected results

|  |  |
| --- | --- |
| **Feature** | **Expected Outcome** |
| **Specific Objective 1:** | |
| Sensor nodes | 1. Proper design of the sensor system for the study. 2. Proper selection of the correct sensors 3. Proper design of the network coordinator |
| Early warning system | Alerts the underground miners for exceeding safe air quality thresholds |
| **Specific Objective 2:** | |
| Machine Learning | Predict the underground air condition for future planning and improve the emergency response system. |
| **Specific Objective 3:** | |
| Two-way communication system | Develop a communication system to enhance effective communications during emergencies in the underground mines. |

# 4.2 Proposed work-plan

Table 4 shows the proposed work plan for completing this research successfully. Figure 5 shows the Gannt chart for accomplishing this research.

Table 4: Proposal work plan for the one (1) month research stay

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **S/No** | **Activity** | **Description** | **Duration** | **Expected Outcome** |
| 1 | Familiarization with the lab | Orientation, introduction to the laboratory and the research team, and familiarization with facilities and equipment such as sensors, microcontrollers, NodeMCU, and XBEE modules. | 2 days | Selection and implementation of the appropriate materials and equipment for my project. |
| 2 | Visitation of the underground mines | Visit the underground mines and learn about the existing mines' digitalization system, including sensor node components, router modules, and ground-based stations, and how they work. | 4 days | In-depth understanding of Existing Mine Digitalization Systems |
| 3 | Research set-up | Set up the necessary software and hardware for IoT, AI, and ML research, including integrated sensors, actuators, and edge effectors for underground mining. | 3 days | Successful Implementation of an Integrated IoT, AI, and ML System for Enhanced Underground Mining Operations |
| 4. | Sensor integration | In collaboration with German experts, IoT sensors will be deployed and calibrated in an actual or simulated underground mining environment, involving sensor installation and setting up the communication network for underground connectivity. Collect initial data and perform preliminary analysis. | 5 days | Deployment and Preliminary Analysis of IoT Sensors in an Underground Mining Environment |
| 5 | Development and testing of AI and ML model | Use the computation facilities in Germany to develop AI models for predictive hazard detection and communication enhancement. This will involve training ML models on collected sensor data and developing algorithms for real-time data processing and detecting abnormalities in underground mines. | 5 days | Development and Deployment of AI Models for Predictive Hazard Detection and Enhanced Communication in Underground Mines |
| 6. | Testing the AI models | Test the AI models in a simulated underground environment and make the necessary refinement | 2 days | Refinement and Validation of AI Models through Simulated Testing in an Underground Environment |
| 7. | Documentation | Prepare detailed documentation of the research and present outcomes to the host institution. | 4 days | Comprehensive Documentation and Presentation of AI Model Development and Testing for Underground Mining |

Table 5: Gannt chart for the proposed research stay

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **PROPOSED RESEARCH STAY PROGRAM (Gantt chart)** | | | | | | | | | | | | | | | | | | | | |
| **Week** | **Week One** | | | | | **Week Two** | | | | | **Week Three** | | | | | **Week Four** | | | | |
| **Activity Day** | **Mon** | **Tue** | **Wed** | **Thu** | **Fri** | **Mon** | **Tue** | **Wed** | **Thu** | **Fri** | **Mon** | **Tue** | **Wed** | **Thu** | **Fri** | **Mon** | **Tue** | **Wed** | **Thu** | **Fri** |
| Familiarization with the lab |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Visitation of the underground mines |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Research set-up |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Sensor integration |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Development and testing of AI and ML model |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Testing the AI models |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Documentation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Networking with researchers and students at TU Freiberg & independent research. | Saturdays & Sundays | | | | | | | | | | | | | | | | | | | |

# 4.3: Propose budget

The proposed budget for this research is outlined in Table 6.

Table 6: Proposed budget

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Name** | **Description** | **Unit Cost (KES)** | | **Qty** | | **Total Cost (KES)** | |
|  | Zigbee module | S2C 6.5mW Zigbee 1200 m Bluetooth Wifi Xbee | 6,500.00 | | 3 | | 19,500.00 | |
|  | Arduino UNO | Arduino Uno R3 board | 1,500.00 | | 2 | | 3000.00 | |
|  | Raspberry pi | Raspberry Pi 4 | 13500.00 | | 2 | | 27000.00 | |
|  | Arduino Shield | Arduino Uno shield | 1500.00 | | 1 | | 1500.00 | |
|  | Xbee expansion module | Xbee V03 Expansion shield | 750.00 | | 2 | | 1,500.00 | |
|  | MQ7 | Carbon monoxide gas sensor | 400.00 | | 1 | | 400.00 | |
|  | MQ135 | Carbon dioxide sensor | 400.00 | | 1 | | 400.00 | |
|  | DHT11 | Temperature and humidity sensor | 650.00 | | 1 | | 650.00 | |
|  | SD011 | Particulate matter Sensor | 4000.00 | | 1 | | 4000.00 | |
|  | BMS Board | 3s 40 A | 800.00 | | 3 | | 2400.00 | |
|  | Fiber wire | 30 m | 300.00 | | 1 | | 300.00 | |
|  | Jumper wire | Female-Female Jumper Wire 40pcs Dupont | 200.00 | | 2 | | 400.00 | |
|  | Casing Plastic tin | 2 tins | 1000.00 | | 2 | | 2000.00 | |
|  | Wire | Red and Black: 2 m each | 100.00 | | 1 | | 100.00 | |
|  | Jumper wire | Male-Male Jumper Wire 40pcs Dupont | 200.00 | | 2 | | 400.00 | |
|  | Jumper wire | Female-Male Jumper Wire 40pcs Dupont | 200.00 | | 2 | | 400.00 | |
|  | Glue stick | 11mm Hot Melt Glue Stick Rod | 350.00 | | 6 | | 800.00 | |
|  | LED |  | 10.00 | | 1 | | 20.00 | |
|  | AC power supply | AC 220V TO DC 12V 5A Transformer Power Supply | 2,200.00 | | 1 | | 2,200.00 | |
|  | Electronic cables | 1.5 mm electronic cables (red, black, and blue) | 300.00 | | 1 | | 300.00 | |
|  | Buzzer/Alarm | Piezo Buzzer | 140.00 | | 3 | | 420.00 | |
|  | Solder wick | Solder Wick AT1515 | 200.00 | | 2 | | 400.00 | |
|  | Soldering wire | 1.0mm 100G Rosin Core Solder 63/37 Wire | 1,000.00 | | 1 | | 1,000.00 | |
|  | DC to DC Converter | 5A DC-DC XL4015 Adjustable Buck Module | 500.00 | | 4 | | 1,500.00 | |
|  | Double sellotape |  | 350.00 | | 1 | | 350.00 | |
|  | Lithium batteries | 18650 | 100.00 | | 30 | | 3000.00 | |
|  | Switches |  | 3500.00 | | 2 | | 7000.00 | |
|  | Media Converter |  | 1000.00 | | 2 | | 2000.00 | |
|  | PCB Board | 7\*9cm Universal Board double-sided PCB | 150.00 | | 4 | | 600.00 | |
|  | IP phones |  | 6500.00 | | 2 | | 13000.00 | |
|  | Miscellaneous |  |  | |  | | 6,000.00 | |
| **Total** | | | |  | |  | | **102 540.00** |

## 

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