DEVELOPMENT OF SITUATIONAL AWARENESS PLATFORM FOR THE SAFETY IN MINING

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

B.RAMESH

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING
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JUNE 2021

DECLARATION

by the Ph.D. Research Scholar

I hereby *declare* that the Research Thesis entitled **Development of Situational Awareness Platform for the Safety in Mining** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirement for the award of the Degree of **Doctor of Philosophy** in the Department of **Electrical and Electronics Engineering** is a *bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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Place: NITK Surathkal
Date: 14-06-2021

CERTIFICATE

This is to *certify* that the Research Thesis entitled **Development of Situational Awareness Platform for the Safety in Mining** submitted by **B.Ramesh** (Register Number: 123010EE12P01) as the record of the research work carried out by him, is *accepted as the Research Thesis submission* in partial fulfillment of the requirements for the award of degree of **Doctor of Philosophy**.

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Abstract

Mining Industry has several safety requirements as per the regulations laid down by the government and other agencies. The environmental impact of the mining industry is one of the important aspects which needs to be monitored continuously as its impact concerns the health and safety of workers as well as residents. The gas samples from the mine area are generally drawn and checked for oxygen, methane, CO2, and CO gas. More methane gas in the absence of proper ventilation can cause severe health hazards to miners. Any deviation in the composition of the atmosphere especially in methane or CO could be sensed early and any untoward incidents like explosion or fire breakout could be prevented.

The center of the study is to monitor, update, analyze and respond to a situation in and around mines. the center of the study conducted. To monitor the situation, sensor networks are utilized. The data from sensor networks helps to monitor the environmental parameters. Wireless Sensor Network (WSN)s are useful in many fields such as coal mine safety monitoring, agriculture management, healthcare, and also for vehicle monitoring.

Sensor data collection using different embedded sensors, ARM7 microcontroller, and Zigbee is studied. The use of Arduino microcontroller board for monitoring is also studied. The study is mainly to monitor the parameters in the deep mining environment.

The possibility of remotely monitoring updating and controlling the mining environment using Raspberry Pi is studied. The use of sensors and Thingspeak to get the sensor data on the web and to obtain its graph in real-time is explored. Then the controlling of the raspberry pi with the help of XBee communication and remotely controlling with the help of a computer is

studied. This is done for the moisture level control using a relay and pump as an example. This method has also other applications. Making use of other types of sensors that are relevant for the mining environment, monitoring and control can be achieved.

To analyze the situation, the data of five parameters namely Carbon Monoxide (CO), Sulfur Dioxide (SO_2), Particulate Matter 10 (PM10), Particulate Matter 2.5 (PM2.5), and Ozone were analyzed for the year 2018 and 2019 for Singrauli of Madhya Pradesh state, where 10 open pit mines are operating. For Talcher of Odisha state, where deep coal mine is operational, the analysis was performed for the year 2019. The analysis is performed using different machine learning techniques like neural network curve fitting analysis and Self Organizing Maps.

Graphical User Interface is developed using Matlab software to analyze the data and to display the environmental situation. This is done for both locations. The analyzed situation is tabulated for both locations.

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Abbreviations

ANN- Artificial Neural Network

ADC-Analog to Digital Converter

CO- Carbon Monoxide

CPU-Central Processing Unit

ELM-Extreme Learning Machine

KNN- K Nearest Neighbor

LPG- Liquefied Petroleum Gas

NN- Neural Network

PM10- Particulate Matter 10

RISC-Reduced Instruction Set Computing

SO_2- Sulfur Dioxide

SOM- Self Organizing Map

SLFN-Single hidden Layer Feed-forward neural Network

WSN- wireless sensor network

Chapter 1

Introduction

The environment pollution control is of paramount importance in the analysis of atmospheric conditions. The sad demise of several workers in the city of New Delhi due to carbon monoxide CO inhalation during the year 2019, has led to believe the significance of this study. The measurement and analysis of atmospheric conditions of hazardous industrial environments are very important for the safety of personnel. Safety will be compromised if these pollutants are not monitored in and around hazardous industries.

To provide support to the workers with special needs in their daily life and also to control automation, the mining industries have taken several steps recently (Islam, 2016). Coal mining industries embody this vision in several ways because sensors are embedded into everyday environmental activities to collect data that monitors the state of the physical environment and its residents when everyday routines are performed. Then the computational component reasons about the collected information to take an action which optimizes the goals such as safety, productivity, and comfort (Acero, 2014)(Li, 2008).

The coal mining industries are constantly driven by the need to increase worker's safety, enhance mining productivity, and achieve environmental sustainability (Singh, 2005), (Duin 2013). Generally, workers are required to work in a hazardous environment and manually control the equipment at close range to ensure the efficient operations of the mining process (Wallace

2015). The complexity of the manually operating equipment of this scale has led to the full productivity of long-wall systems not been achieved. The hazardous or harsh working environment has potential health and safety concerns for mining workers. Safety in the coal mining industry should be taken very seriously. It is necessary to report annual figures of fatal and non-fatal incidents as per the regulatory board.

Deep mining has issues related to ventilation and mine collapse which are complicated to handle. There is a possibility of a mine collapse in some cases. The safety risk will be there in all types of mining due to the use of heavy machinery. To avoid explosions, methods are necessary to remove methane before and during excavation. The SO_2 emissions from major coal mines in India are indicated in Figure 1.1. Particle matter(PM) is another important pollutant which if not controlled, might lead to breathing problems and other health issues.Components of particulate matter (PM) include finely divided solids or liquids such as dust, aerosols, smoke, fly ash, fumes, soot, mists and condensing vapors that can be suspended in the air for extended periods.

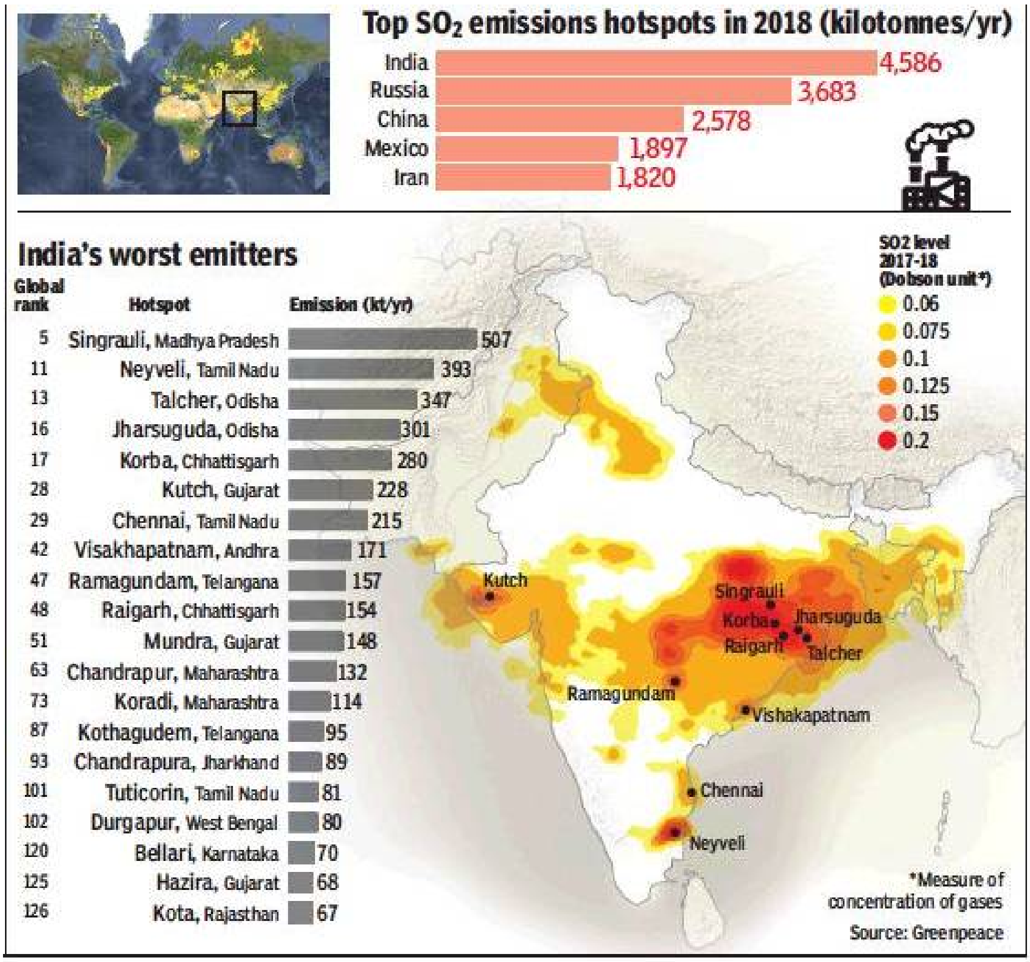


Figure 1.1: SO_2 emissions from coal mines (Greenpeace)

The measurement and analysis of atmospheric conditions of the hazardous industrial environment are very important for the safety of workers. Safety will be compromised if these pollutants are not monitored in and around hazardous industries. The air quality is an important parameter in and around the opencast coal mines like in Singrauli. Singrauli district is located in the state of Madhya Pradesh. There are ten mostly mechanized open cast mines in Singrauli (NCL Ltd, 2020).

Figure 1.2: Coal Mine

Current improvements in pervasive computing and sensor technologies have allowed the contextualized enhancement of business processes capitalizing on the capability to perceive, process, integrate and interpret the data of various modalities. Out of the many areas of interest, the representation and recognition of situational events of worker's safety is a prominent instance where pervasive computing environments deliver exclusive results for the contextualized monitoring and assessment of behavior or event, such as the coal mining environment.

The latest advances in wireless communication technologies and micro-electro-mechanical systems have led to great progression in wireless sensor networks(WSNs) (Baronti, 2007). WSNs are wireless networks that consist of many spatially distributed sensors with limited processing capability and data gathering to monitor the environmental condition. Because of their ability to monitor and manage situational information for various intelligence services, these networks have become more important (Yick, 2008). Therefore, the WSNs have been applied in various fields such as Coal Mine Safety Monitoring System, healthcare monitoring, and military applications(Alemda, 2010).

Sensors in the monitoring environment are embedded anywhere and on any objects or human bodies (Cheng 2013), (Teizer, 2015). They collect the data containing the user's motion, location, environmental temperature, activity information, humidity, and ambient noise level (Gaddam, 2011). Applications that provide customized services to the users are based on this sensor data. However, sensor data exhibits high complexity (huge volumes, different modalities, and interdependent relationships between the sources), dynamism (real-time update and critical aging), precision, timeliness, and accuracy (Cheng, 2017). A prevalent computing system should not examine itself with the separate pieces of sensor data rather than the information should be interpreted into a higher domain-related idea. This higher-level concept is a situation, which is an abstract state of affairs interesting for the various applications (Corchado, 2010)(Ye,2012).

The ability to use situations lies in their capability to give a simple and human-readable presentation of sensor data to applications, although shielding applications from the complexities of sensor readings, sensor data noise, and inference activities and simultaneously leveraging the structure implicit in the activities are being observed (Chaaraoui, 2012). Situation recognition is the process of identifying interesting status automatically and changing the physical environments or the entities. With the advancement of context-aware applications in smart spaces, situation recognition is regarded as a sound method to offer constantly changing situational pictures about the observed environment (Loia et al. 2015).

The system has a significant task of defining and managing the situations. This includes capturing what and how situations are to be recognized from which pieces of contexts and how different situations are related to each other (Learner et al., 2010). Context-aware modeling techniques should be able to understand by the available context sources, their data structure and automatically built internal data models to facilitate them. Additionally, raw context needs to be retrieved and transformed into appropriate context representation models accurately with minimum human intervention. Many popular context modeling techniques are utilized to give a representation of the sensor data. Context models can be static or dynamic. Static models have a predefined set of context information that will be collected and stored (Mormul et al., 2017). The requirements needed to be taken into consideration when modeling context information are mobility and heterogeneity, dependencies and relationships, imperfection, reasoning, timeliness, efficient context provisioning, and usability of models (Yurur et al., 2014).

Low-level sensing data obtained from the smart environment (e.g., coal mining environment) is an important source of information for situation recognition. But, the main problem of sensor-based event recognition is the data obtained from sensors have different degrees of dynamics and uncertainty (Liu et al., 2016). This uncertainty arises for several reasons in a sensor network environment such as inaccurate measuring, fault sensors, and "dirty" data corrupted by wireless networks owing to network problems (Khan et al., 2012). There are various data-driven techniques (Li et al., 2017) such as Machine Learning algorithms (Cao et al., 2008) and Meta-heuristic optimization aided learning-based techniques (Chou and Thedia, 2016) which are employed to recognize sensor events in the coal mining environment.

A vital challenge in situation representation is the capability to efficiently combine manifold sources of heterogeneous, noisy, and possibly inconsistent data in a way that delivers precise and valuable results. For the representation of heterogeneous sensor data, the knowledge and data-driven approaches are presented in earlier researches. Data-driven approaches relied on probabilistic and statistical models to represent activities. On the other side recognizing the situations from deep mining environment various machine learning techniques are utilized like curve fitting, self-organizing map (SOM), and extreme learning machine.

1.1 Situational Awareness

Web Reporter Most nodal centers are lacking two key inputs new leads on unknown issues and ground-level vision through close-up still photos and videos. With situation awareness (Figure 1.3), there is a quick and targeted way for skilled personnel to share valuable data on time. Before, radio communications by a qualified responder were the only way to get perspective from the site. A majority of mining employees are equipped with smart devices and reliable connectivity which can help produce a new level of insight for the nodal center. With web Reporter, one can quickly seize the most important information, share it with the local nodal center, and stored it as on-the-scene footage which is typically unavailable.

Figure 1.3: Situational Awareness

Analyzer

With numerous communications and data input being presented to the sender, there is now a comprehensive way to sense, filter, and analyze timely information and permit actionable responses. With a mapped situation, comprised of surveillance, sensors, and databases, the analyzer is empowered with a correct picture of how the responders are positioned to react.

Responder Normal response schemes connect radio-bound emergency responders back to the emergency control center to keep track of resources that can respond to an incident. The responder can find out where are the resources and their status which brings a wide-ranging view to their fingertips.

1.2 Structure of Report

The structure of the report is as follows. After the introduction and overview of related works in chapter 1, details regarding the different approaches by various researchers regarding the safety in mining and pollution due to mining are discussed in chapter 2. This chapter is followed by chapter

3, in which extensive study is performed on methodologies to collect data using different sensors, microcontroller, and processors. This chapter also covers how it is possible to communicate with the mining environment from the nodal control room using XBees and the Raspberry pi. In chapter 4 aims to answer the question of whether it is possible to use curve fitting and SOM models trained on different sensor reading data-sets to make accurate clustering and analysis to predict a dangerous situation. In chapter 5, the results obtained from the above techniques are discussed. Finally, in chapter 6, the conclusion and future scope of the study are discussed.

Chapter 2

Comprehensive Literature Survey

Some of the recent research works related to the situation representation and recognition of WSNs in coal mining environment is reported below:

Bhattacharjee S et al.(2013) have presented the response time of the developed system for identifying fire in the Board and Pillar coal mine panel. It uses WSN to observe the exact fire location. In the developed system, the two sensor nodes located at the panel inlet and outlet will detect carbon monoxide and oxygen gas concentration continuously. The output of the two sensor nodes will be given as the input to the controller node which is responsible for calculating the difference between the ratio of carbon monoxide and oxygen concentration of the inlet and outlet signal. A threshold limit will be put in the controller node. When the output of the controller node crosses the threshold value, it will first generate an alarm which will be the indication of the occurrence of fire in that working panel. It will result in the activation of the temperature sensor nodes to recognize the exact fire location. The performance of the developed system has been determined via rigorous simulations. The simulation results reveal that the average network delay changes almost linearly with the increase in the number of hops.

The CO lower tropospheric strengths and total columns can be matched with independent measurements. The global dispersals of CO are finally presented by Abu et al.(2011) and deliberated with the assistance of simulations.

Wei Chen et al.(2016) have analyzed the structural features of the coal mining tunnel based on the Bayesian decision technique and minimum error Bayesian decision technique. Following the probability of working objects on the choice between the cross-ways and the tunnels, they propose the prediction approach for selecting the path based on the Bayesian decision, the associated nodes in the branch, and the tunnel of the mining area. Based on the conditional probability and the prior probability of the active objects on the tunnel, they can estimate the posterior probability of tunnel selection and also predict the selection probability of the miners on the tunnel in the next moment. This method is the basis for the correlation among the network nodes which can reduce the monitoring nodes, lock the important nodes and improve the accuracy in detecting and tracking the active objects. In the decision-making of predicting the selected tunnel of moving target, one method can make the error rate of decision-making minimum. This method can provide a theoretical basis and techniques for monitoring the coal mine safety to prevent and disclose the hidden hazards of the coal mining environment. Experimental results showed that the Bayesian decision technique can effectively connect the nodes.

The environmental impact of drilling equipment is determined in a surface coal mining operation. The approach used in this paper allowed the determination of exhaust and dust emissions, and sound pressure level. Modeling of the environmental impact of the equipment was conducted using the Microsoft Visual Studio.NET software package.[9].

Emissions of CO from fuel use in China, a country that accounts for a significant fraction of total Asian emissions and where there has been a rapid growth in the industrial and transportation sectors. are estimated to have increased by only 16 Tg yr-1 between 1990 and 1995 due to almost no change in the relatively large bio-fuel combustion source. Thus it is also unlikely that a significant portion of the discrepancy between the top-down and bottom-up estimates in Asia can be explained by growth in Asian CO emissions from 1990 to 1994.[10].

Minhas U I et al.(2017) have proposed a WSN-based system for monitoring and event reporting in underground mine environments. The proposed system which is capable of detecting and identifying events of interest (with

90% success rate) and localization of miners (2-4 m) and roof falls (10-12 m). Moreover, a novel energy-efficient hybrid communication protocol using both periodic and aperiodic modes of communication while adhering to low latency requirements for emergencies is proposed and implemented. Finally, for intelligent processing of gathered data, a Spatio-temporal and attribute-correlated event detection mechanism suitable for the highly unreliable mine environment is described. The system successfully detected and identified the events in all tested cases, providing a comprehensive control & monitoring mechanism, tracked the location of miners and events required for rescue operations.

For comparison, CO concentrations were measured over continental areas in Brazil. Much larger values have been found in moderate 'burning' regions, such as the south of the state of Mato Grosso and the north-western part of the state of Parana, where 200 ppbv in the dry season has been observed. Since normally the air masses have traveled for several days over the ocean, the air masses over the site present low chemical activity. Daily variations of CO2 are very small, of the order of a few percent relative to the diurnal mean (Kirchhoff et.al, 2003. CO discharges from vehicles, petrol, and diesel generators, show a concentration of carbon monoxide that is highly contaminated. It is good to stay away from these sources. CO will be emitted into the atmosphere when fossil fuels are used to run the vehicles and generators whereby the unsafe condition prevails(John and Feyisayo, 2013). The possibility of using satellite images to measure contaminants in natural conditions and large urban areas and even countries are explored. The use of this information helps to reduce the costs and labor compared with land-based techniques. The convenience of satellite services in the terrain helps in reducing the cost of air pollution checks by the use of satellite imagery (Hamzeloa et al.,2015). The lung performance of non-coal personnel was better than the of coal personnel(Sarwa et al.,2017). The authors recommend further study with regards to this work.

Additional air pollutants emanated comprise SO2 and NO2 produced from the furnace and drying procedures. SO2 is produced from the sulfur composites in the combusted fuel. The burning of coal in revolving cement

kilns produces NO2 from the nitrogen in the coal and incoming ignition (Barret et.al, 2015). Detecting air pollution from space can observe drifts and deviations of atmospheric toxins affecting human health. The detection of air pollution over the cities, with satellites, has the challenge of low CO sensitivity of measurements(Borsdorff et al., 2018).
Mishra and Das (2020), observed that the mining-affected villages witnessed different types of environmental issues. With increased production of coal, the environment of mining-affected villages is degrading in a fast manner.

Environment monitoring using both Raspberry Pi and Aurdino with wireless sensor networks is proposed by Ferdoush (2014). For exterior and offline analysis purposes, the data can be taken from the Thingspeak database as CSV or Jason or PHP format(Jang et al. 2015). It was proposed to build gateways for IoT with Raspberry Pi. Low power wireless packet communication RF modules provide components to build IoT applications quickly and easily (Calvo, 2016). Using wireless communication, sending environmental parameter data from sensors located in mines and transmitted to the control room was proposed by Ledange (2016). Suggestions to design a wireless sensor network making use of a microcontroller that can observe the different parameters like humidity, methane, and carbon dioxide in an underground mine were proposed by Dange and Patil (2019).

Cheng et al.(2017) have proposed a uniform message space and data distribution model and also a lightweight service mashup approach. With the help of visualization technology, the graphical user interface of different underground physical sensor devices could be created, which allows the sensors to combine easily with other resources. The proposed mash-up middleware is to improve the coal mine monitoring and control automation, which allows the user to create the ad-hoc safety monitoring and automation service intuitively. Cheng et al. had proposed a solution that includes four phases: 1) to access the sensor data with OSGi-based uniform devices access framework; 2)to adopt the publish-subscribe mechanism to distribute the sensor data; 3)to implement a lightweight services mash-up approach that supports the on-the-fly integration of different services to build comprehensive and situational applications, and 4)to apply the REST principles to define an extensible interface for end-users. The proposed solution is easy to deploy and implement quickly and may help to improve the coal mine safety monitoring and automation level.

In the work conducted by Sugumaran et al.(2017), the images and videos from the mining area are sent to a cloud server. If the server is not accessible, the data could be stored locally in the Raspberry Pi and transmitted when the link is re-established. By this, home monitoring is made easier. Raspberry Pi can be used for smart purposes and client-server communications. The various attributes available in Raspberry Pi are introduced by Zhao et al. (2015). The possibility of live sensor data transmission from raspberry pi to Ubuntu operating system using ZigBee technology is explored by Mala et al (2017). An autonomous robot that can recognize commands provided by the hand gestures is exhibited with a help of a microcontroller and an accelerometer by Kausthub et al (2016). A powerful system using Raspberry Pi as an intelligent device using which numerous things can be interconnected and can be managed from an extended range was proposed by Vimal et al. (2019).

Janusz A et al. (2017) have investigated and compared the practical approaches for determining the seismic events by using the analytical models constructed based on domain knowledge and the sensor data. For the case study, they used a rich data set gathered during five years period from various active Polish coal mines. They mainly focused on comparing the prediction quality among the expert methods which serve as a standard in the coal mining industry and state-of-the-art machine learning methods for mining high-dimensional time series data. They described an international data mining challenge organized to facilitate the study and also they demonstrated a technique that is employed to construct an ensemble of regression models able to outperform other approaches used by the participants of the challenge. Finally, they explained how they utilized the data obtained during the competition for research on the cold start problem when deploying decision support systems at new mining sites.

Several companies developed mesh systems that use discrete signal relay points (nodes) placed throughout the mine that will communicate with handheld devices on miners and with other nodes (Figure 2.1).

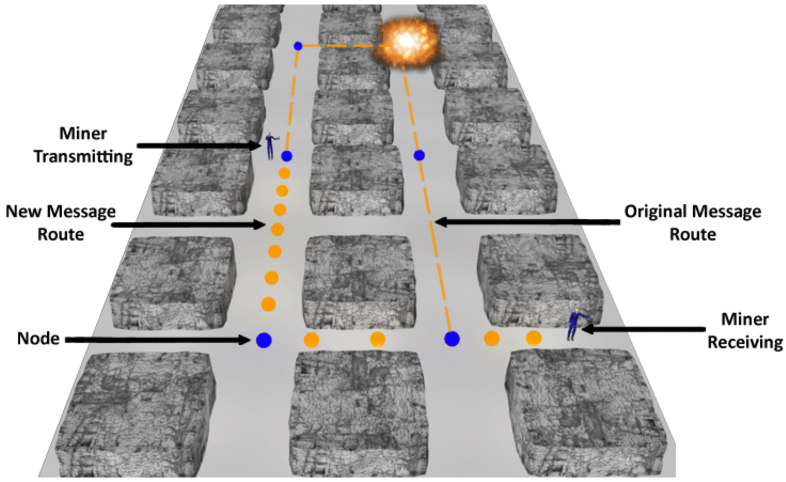


Figure 2.1: Node based system (Novak, 2010)

In a true mesh system, all nodes would be able to communicate with all other nodes in the system, but in a coal mine, this would be impossible due to thousands of feet of rock blocking signal propagation. A more accurate description would be partial mesh, where any node can communicate with any other node in the working range (Novak et al., 2010).

2.1 Data Management

A prevalent computing system should not examine itself with the separate pieces of sensor data rather than the information interpreted in higher domain-related ideas. This higher-level concept is a situation, which is an abstract state of affairs interesting for the diverse applications (Ye et al. 2012). The ability to use situations lies in their capability to give a simple and human-readable presentation of sensor data to applications, although shielding applications from the complexities of sensor readings, sensor data noise, and interference activities (Chaaraoui et al., 2012).

The article by Calvo et al. (2016) solves the research question of how to build gateways for IoT applications with Raspberry Pi and low power communication modules. Its major outcome is providing application designers all components to build IoT applications quickly and easily.

Dange and Patil (2016), propose a design of a wireless sensor network (WSN) with the help of an MSP430xx controller which can monitor the temperature, humidity, gas, and status of smoke in an underground mine. A design is proposed which is made of different sensors which will sense the environmental parameter in underground mines and this parameter data is sent to the control room using wireless communication protocol ZigBee (Ledange et al., 2016).

2.2 Situation Control

An autonomous robot that can recognize commands provided by the hand gestures was exhibited with a help of a microcontroller and an accelerometer (Kausthub et al., 2015). A metering device which senses and sends the reading by use of ZigBee which is then processed and the data is sent for billing purpose was proposed (Chaudhary et al., 2016). The possibility of live sensor data transmission from Raspberry Pi to the Ubuntu operating system using ZigBee technology is explored (Mala et.al., 2017). A powerful system using Raspberry Pi as an intelligent device using which numerous things can be interconnected and can be managed from an extended range was proposed (Vimal et al., 2019).

The use of Raspberry Pi and PIR sensors was investigated by Sugumaran (2017). Using wireless communication, sending environmental parameter data from sensors located in mines and transmitted to the control room was proposed (Ledange et al., 2016). As the multiple sensor data need to be analyzed using advanced techniques, the data can be exported to the Thingspeak database the data can be imported from the ThingSpeak database as CSV or Jason format as batch files(Ferdoush et al., 2014)

2.2.1 Data Analytics

Capturing what and how situations are to be recognized from which pieces of contexts, and how different situations are related to each other is important. Context-aware modeling techniques should be able to understand the available context sources, their data structure and automatically built internal data models to facilitate them (Soldatos et al., 2007). Raw context needs to be retrieved and transformed into appropriate context representation models accurately with minimum human intervention. Many popular context modeling techniques (Makris et al., 2013) are utilized to give a representation of the sensor data. Context models can be static or dynamic. Static models have a predefined set of context information that will be collected and stored (Lukowicz et al., 2012). The requirements needed to be taken into consideration when modeling context information is mobility and heterogeneity, dependencies and relationships, imperfection, reasoning, timeliness, efficient context provisioning, and usability of modeling formalisms (Yurur et al.,2014).

2.3 Research Motivation and Objectives

2.3.1 Research Motivation

The following points are the motivation for this research work.

Firstly, the recent developments in the internet of things and the embedded sensor circuits, and several types of microcontrollers and dedicated microprocessors have led to many methods of collecting data from hazardous environments using smaller devices and circuits which are portable or which take very little space. This is especially useful in space-constrained hazardous industries. The different sensors which can be used are studied. Then some industrial-grade sensors which can be used in the mining environment are discussed. Some of the processors which can be used for these constrained space applications were studied.

The developments in cloud storage and web-based data visual display have made data management very appealing and very helpful in internet-of-things (IoT)based applications which can be applied very effectively to hazardous industries like mining, refineries, power generation, and railways. These methods are very much in the fast developmental stage as many companies are providing web-based services for the researchers. One method of visually displaying different sensor data using the Thingspeak website (subsidiary service of Matlab) is developed in this thesis work.

Secondly, when there is a fire break-out or some other situation that might damage the cable. For this purpose, it is necessary to have wireless communication between the environment and the nodal control room. The data from the sensors used to measure different parameters could be directly uploaded to the ThingSpeak website, where it can be saved as well as the visual display of the data could be obtained. Wireless communications like Wi-Fi, Zigbee, and XBee can be effectively used to alarm or controlling the hazardous environment. This technique is effectively used in the research work where the possibility of water level control is done in a hazardous area using XBee communication from a remote computer and Raspberry Pi.

Finally, the data analytics is applied to the collected sensor data. These techniques are still under the exploratory stage. The different techniques like self-organizing maps, neural network curve fitting, and extreme learning machine are still under the exploratory stage, due to the availability of high-speed processors. Due to these developments, many researchers are working in the field of machine learning and big data analytics. Data analytics methods are explored in this research work and put for field use. The graphical user interface is developed which will perform neural network analysis on the available real repository data and gives output depending on the situation surrounding the hazardous environment. The SOM technique gives the clustered output. The curve fitting technique will provide the error values for a given set of data.

2.3.2 Research Objectives

Based on the research motivation, the objective of the thesis is to concentrate on the combination of hardware and software part of the following issues:

- Sensor data collection, data transmission, and data management incorporating embedded system development platform.
- Situational management namely controlling and alarming using wireless communication.
- Data analytics using neural network techniques.

Chapter 3

Development of Embedded Systems to host Situational Awareness Platform

3.1 Data Collection Techniques

It is essential to build up and attain the automatic and real-time sensing for various parameters and indexes of the mine based on the recent communications technology and equipment, with computer technology.

DHT11(DHT11 2010) is a combined digital temperature and humidity sensor. The sensor comprises a calibrated digital signal output of the temperature and humidity. As per the manufacturer, due to dedicated digital module collection expertise, it ensures better reliability and good long-term steadiness. The data transmissions by DHT 11 is indicated in Figure.3.1

- Humidity Range: 20-90 % RH
- Humidity Accuracy:±50 %
- Temperature Range:0- 50°C
- Temperature Accuracy:± 2 %
- Operating Voltage: 3V to 5.5V

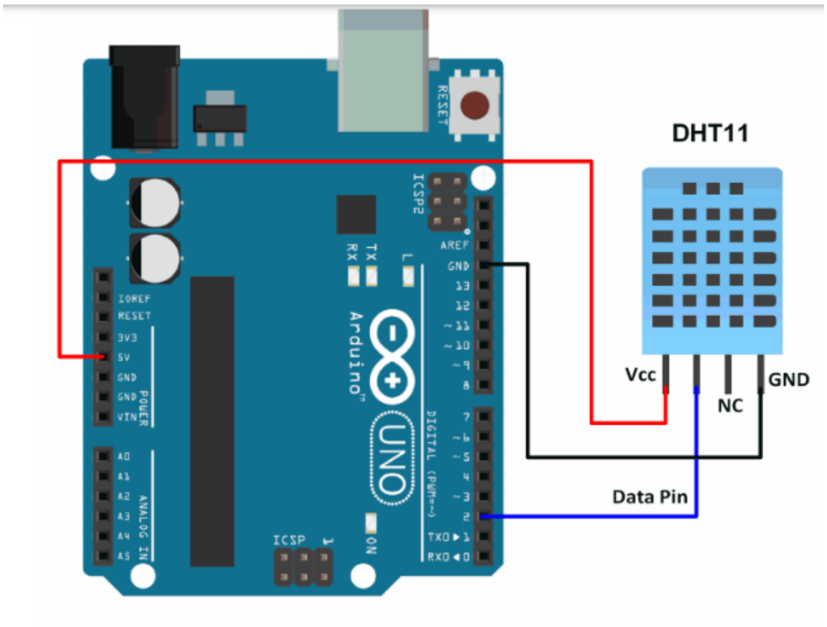


Figure 3.1: DHT 11 Signal

With the ARM 7 microcontroller (Arm 7, 2010), the temperature and humidity sensor DHT11 is connected and the collected data is transmitted by ZigBee wireless communication. The result obtained is as shown in Figure.3.2.

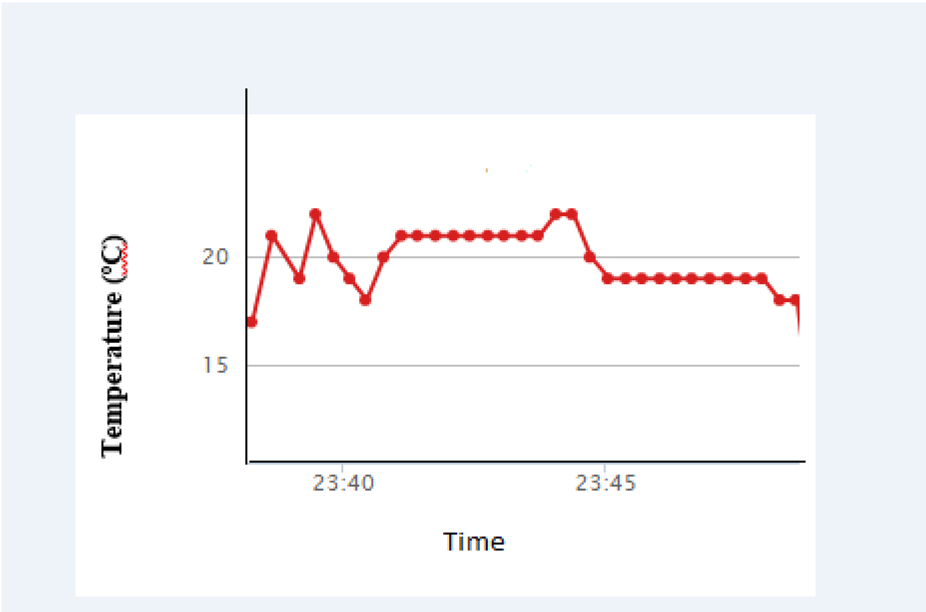
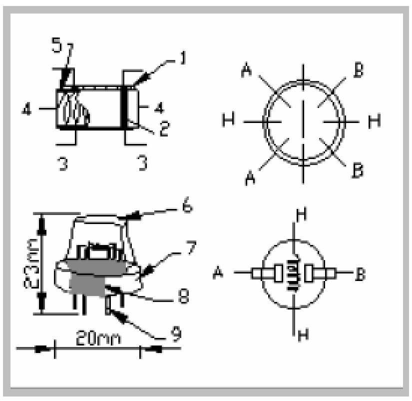


Figure 3.2: DHT 11 Signal

The MQ-7(MQ7 2012) is a Carbon Monoxide (CO) sensor appropriate for sensing CO concentrations in the atmosphere. It makes detection by method of cycle high and low temperature, and sense CO at low temperature. It is extensively used in household CO gas leakage alarms, industrial CO gas alarms, and portable CO gas detectors (Figure.3.3).



	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni

Figure 3.3: MQ7 Configuration

The soil moisture sensor comprises two probes that are used to gauge the water content. The two probes allow the current to pass through the soil and then it analyses the resistance value to get the water content. When there is excess water, the soil will conduct more electricity resulting in less resistance. This indicates higher moisture content. Dry soil's conductivity is less due to lower water content, resistance will be higher.

The Arduino board used here comprises of ATmega 328 (Arduino,2009). It is a low-power CMOS 8-bit microcontroller based on the enhanced RISC architecture. By executing dominant instructions in one clock cycle, the ATmega328 realizes throughputs of about 1MIPS per MHz. This enables the system designer to improve the device for power consumption versus processing speed. Each of the 14 digital pins on the Uno can be used as an input or output, using pinMode(), digitalWrite(), and digitalRead() functions. They operate at 5 volts. Each pin can provide or receive a maximum of 40 mA and has an internal pull-up resistor (disconnected by default) of 20-50 kOhms. Besides, some pins have specialized functions.

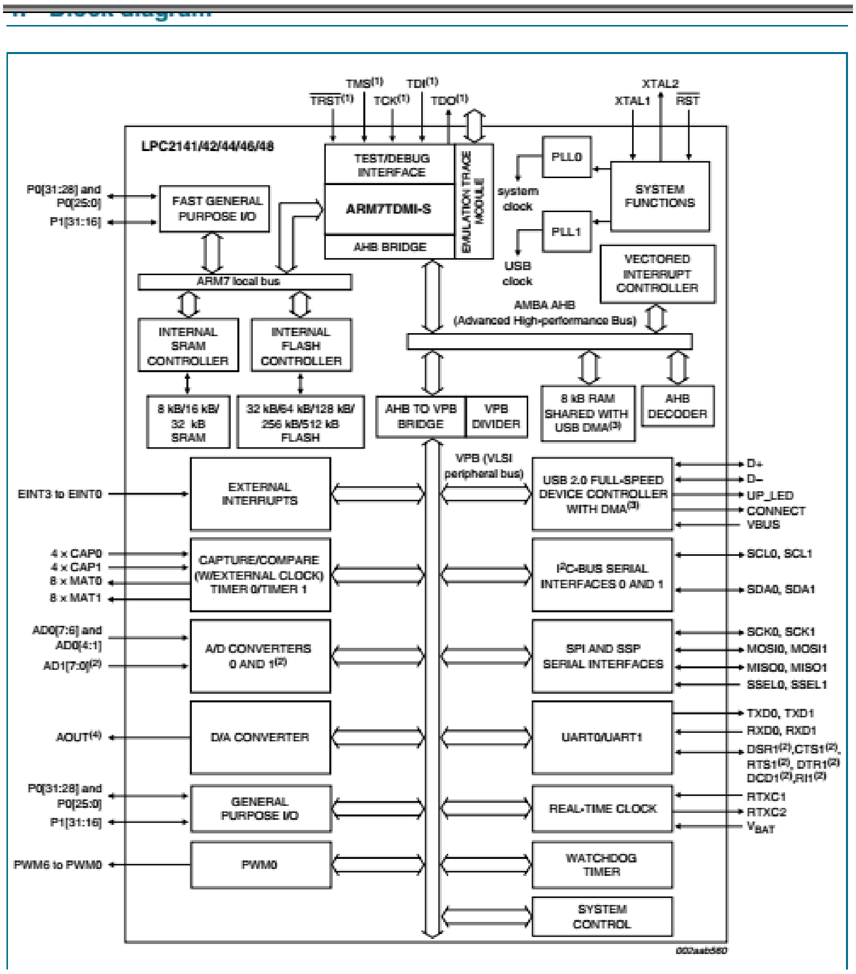


Figure 3.4: Block diagram of ARM7 Microcontroller

3.1.1 ARM 7 Microcontroller Circuit

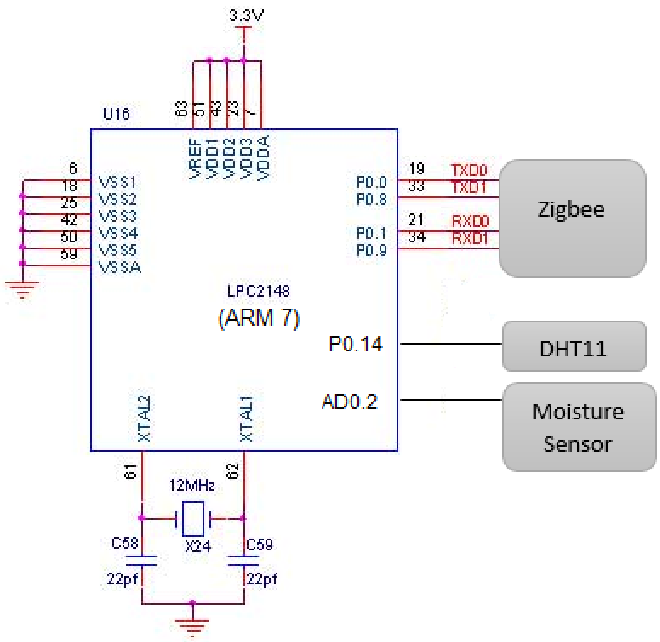


Figure 3.5: ARM 7 connection diagram

The possibilities of using either the arduino or ARM 7 microcontrollers for the situation awareness are studied (Figures 3.4 and 3.5).

With the ARM 7 microcontroller (Arm 7, 2010), the temperature and humidity sensor DHT11 is connected and the collected data is transmitted by ZigBee wireless communication. The result obtained is as shown in Figure 3.6.

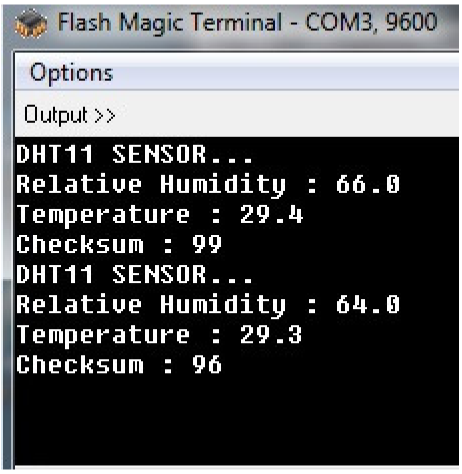


Figure 3.6: Temperature and humidity indication

3.1.2 Arduino Circuit for CO Monitoring

The measurement from the Arduino circuit for the sensing of CO monitoring is shown in Figure 3.7.

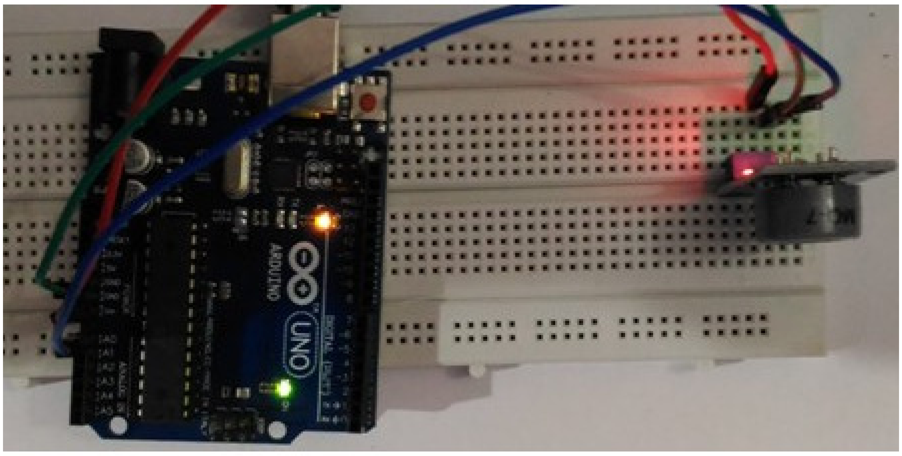


Figure 3.7: Arduino to monitor CO

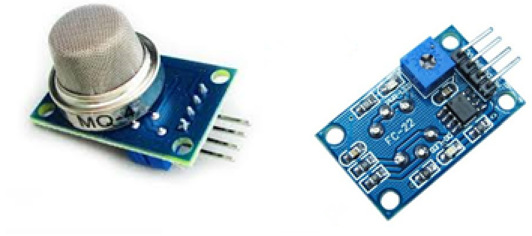


Figure 3.8: Methane sensor

The CO level should be within 0.2 ppm for healthy air. So, the sensor output should be calibrated to trigger an alarm when it crosses this healthy level for more than a certain duration.

3.1.3 Arduino circuit for moisture measurement

The measurement from the Arduino circuit for the sensing of moisture content is shown in Figure.3.9

The measurement from the Arduino circuit for the sensing of moisture content is shown in Figure.3.9

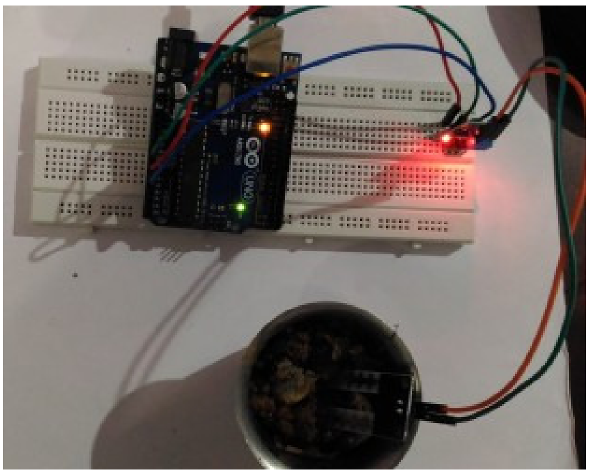


Figure 3.9: Moisture monitoring

To measure the moisture content in a corrosive environment, a capacitive type of moisture sensor is preferred (Figure 3.10). The moisture content will be of importance especially if the soil resistance is of importance for the mining as well as if the soil stability is to be considered.

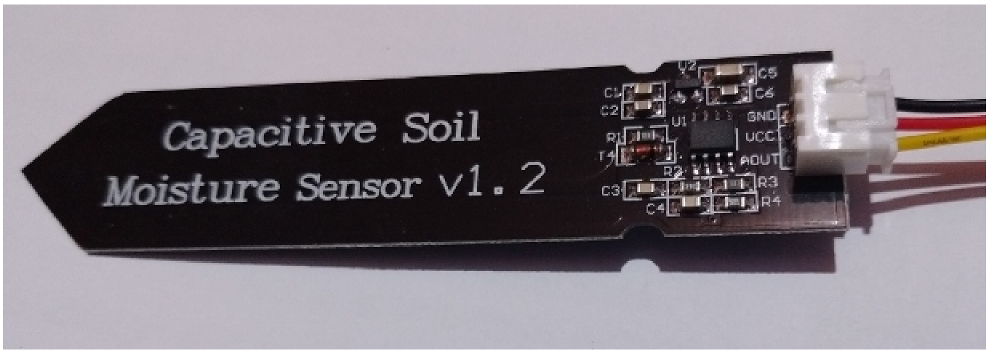


Figure 3.10: Capacitive Sensor

The two possibilities of using ARM 7 and Arduino microcontrollers for safety awareness in a mining environment were studied. It can be observed that ARM 7 gives faster processing but its size is one drawback. This is especially true if it has to be embedded in the helmet. Arduino board provides advantages like a smaller size, lower cost, and easily available programming resources on the internet. It is of better choice if the circuit needed to be fixed to a safety helmet.

Being analog sensors, both resistive and capacitive sensors need to be connected with ADC so that the digital data will be supplied to the Raspberry Pi. Capacitive measuring eliminates corrosion of the probe and gives an improved measurement of the moisture level of the soil. Non-corrosive industrial-grade sensors are necessary for the mining environment.

3.2 Situation Awareness of Mining Environment using Raspberry Pi

3.2.1 Introduction

The gas samples from the mine area are generally drawn and checked for oxygen, methane, CO2, and CO gas. These analysis results are stored for future analysis. More methane gas in the absence of proper ventilation can

Table 3.1: Air Quality Standard (Australian)

item	Pollutant	Averaging period	Max Concentration
1	CO	8 hours	9.0 ppm
2	NO2	1 hr	0.12 ppm
3	SO2	1 hr	0.2 ppm
4	Lead	1 year	0.50 micro-g/m^3

cause severe health hazards to miners. Any deviation in the composition of the atmosphere especially in methane or CO could be sensed early and any untoward incidents like explosion or fire breakout could be prevented. Being lighter than air, methane may get accumulated in some higher mine areas. Oxygen deficient spaces could be created at some higher levels.

Miners should be aware of the different alarm locations and once the alarms are on, these areas should be approached cautiously. Mine fires are difficult to manage. Hence temperature is also an important parameter to measure and monitor. The dust emissions from the mining environment will also create health problems (Table 3.1).

Measuring pressure is important during mining operations since situations in which the barometric pressure either goes too high or drops too low can cause serious safety hazards. As atmospheric pressure increases, air from working areas of the mine will tend to move toward impenetrable areas and into gobs, providing oxygen into those spaces of the mine. An area with a volatile methane and air combination could occur behind seals or on the borders of the gob. Mines with coal that are inclined to impulsive ignition could experience increased carbon monoxide levels.

Health and Safety Problem

The different parameters surrounding the mining environment such as temperature, humidity, barometric pressure, light, methane concentration are sensed using different types of sensors. These sensor data are analyzed using the Raspberry Pi (Raspberry Pi,2016). One data is plotted as a demonstration to indicate that the sensor data can be easily plotted or analyzed using raspberry pi.

3.2.2 Different Embedded Sensors used with Raspberry Pi

Temperature and Humidity sensor

DHT11 is a combined digital temperature and humidity sensor. The sensor consists of a calibrated digital signal output of the temperature and humidity. Due to devoted digital modules collection technology and the temperature and humidity sensing technology, it guarantees high consistency and good long-term stability.

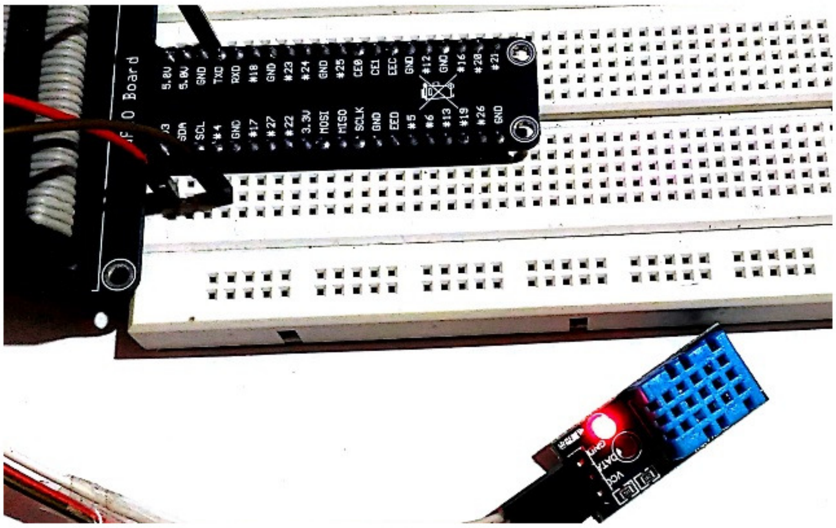


Figure 3.11: Temperature and Humidity measurement

The temperature data was collected and saved as a data file. This saved data is plotted and the variation is observed when the sensor temperature is varied (Figure 3.11).

Pressure sensor

To prevent the hazardous increase in pressure, it is recommended to sample the atmosphere behind seals and check for explosive combinations when there is a release of gases because of increased pressure. It is also necessary to measure the atmospheric system for signs of increased CO concentrations showing a possible rise in temperature in the gob.

Reduced atmospheric pressure can produce methane from the coal layer into the mine atmosphere at an increased rate, and also may appear in areas of the mine not normally known for methane accumulation. Explosive methane/air mixtures may be present in the areas of the seals. It is suggested to develop practices to prevent a drop in atmospheric pressure by making frequent measurements for methane in work areas when the pressure is falling.

BMP180 Barometric Sensor

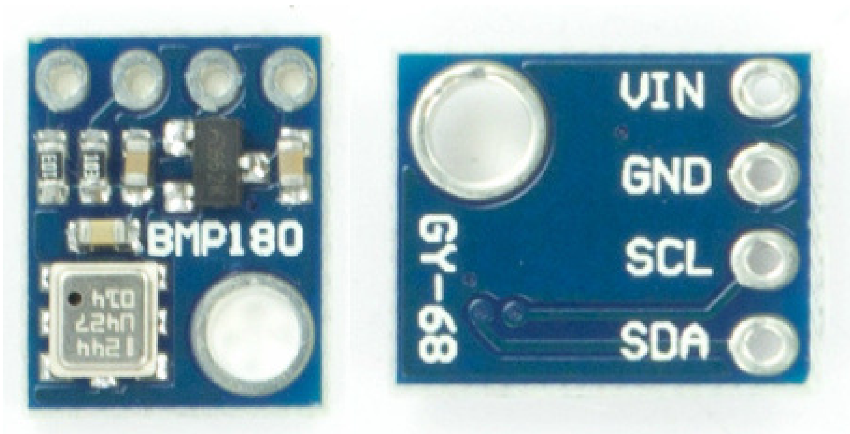


Figure 3.12: Pressure sensor

The BMP180 barometric sensor (BMP180,2015) is as shown in the Figure.3.12. This is a very small module that detects the absolute pressure of the air near it. The BMP180 consists of a piezo-resistive detector (Figure.3.13), an analog to digital converter and a control unit, and a serial I2C interface. It has a detecting range from 300 to 1100hPa with an accuracy of 0.02 hPa. It can also detect altitude and temperature. The BMP180 barometric sensor communicates via an I2C interface.

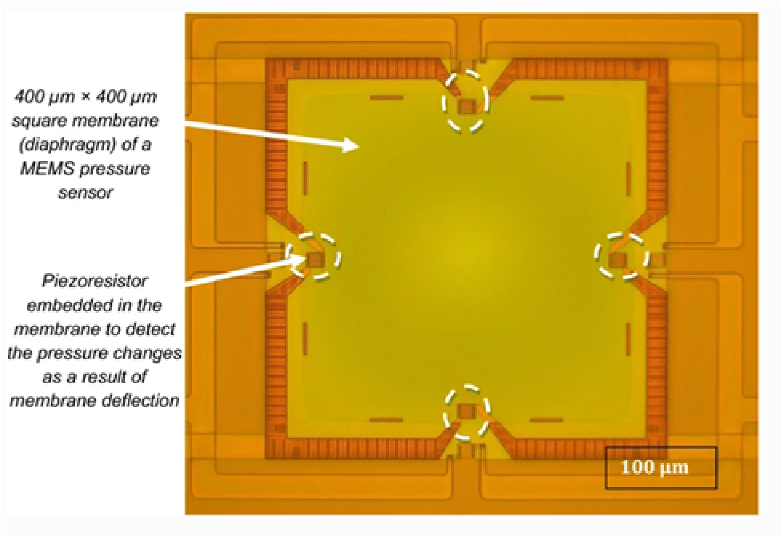


Figure 3.13: Pressure sensing element

The implementation of pressure measurement using BMP 180 is indicated in Figure.3.14.

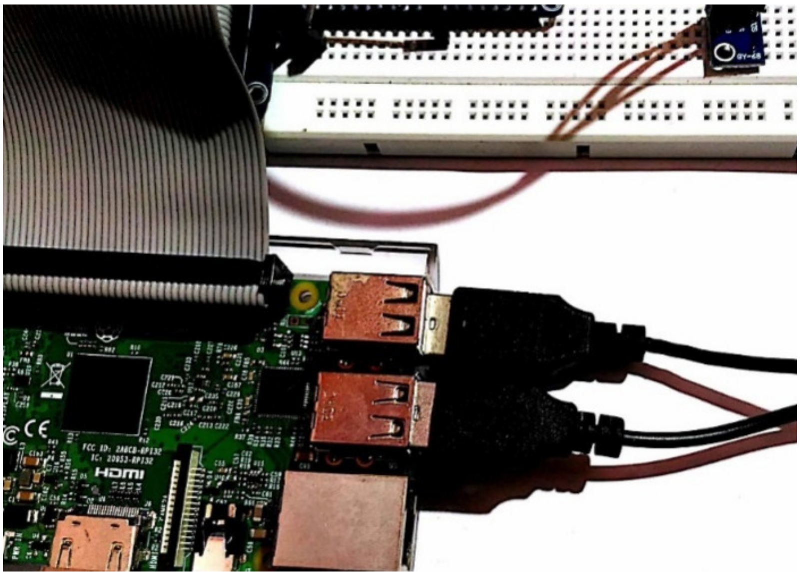


Figure 3.14: Measurement of pressure

When a pressure is applied to the sensor, there is increase in pressure indication as shown in Figure3.15.

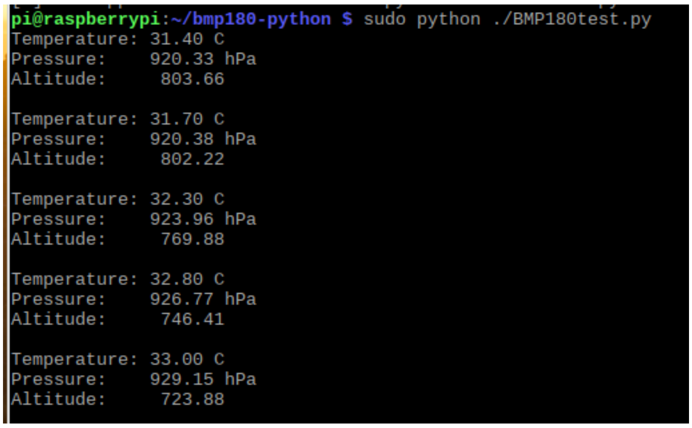


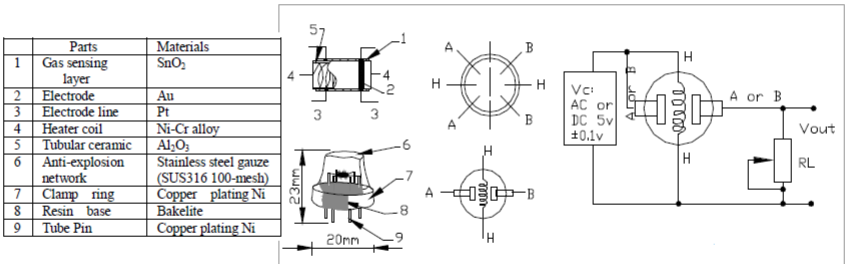
Figure 3.15: Pressure sensor output

Gas Sensor

MQ series sensors use a small heater inside with an electrochemical sensor to measure various gas combinations like LPG, Methane, and CO. For industrial purposes, calibrations are done in specific laboratories with calibrated probes and tests. Figure.3.16 shows MQ4 sensor (MQ4, 2012) which can sense methane / natural gas easily with a range sensitivity from 300 to 10000ppm. Its cost is low and can be easily connected with Arduino or ADC boards.

Figure 3.16: MQ4 gas sensor

This model comes with 4 pins. These are V_{CC}, GND and the other two are 1 pin DO (digital output) TTL digital 0 and 1 (0.1 and 5V) 1 pin AO (analog output) 0.1-0.3 V (clean), the highest concentration of voltage around 4V.



	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni

Figure 3.17: MQ4 Configuration

MQ4 model must be powered with stable 5V and needs at least 150mA according to the datasheet declaration, to be able to work properly (Figure.3.17).

While using the sensor, as the smoke is introduced, it can be observed that there is sudden change in the value of output as indicated in Figure.3.18. This can be used for the alarm purpose.

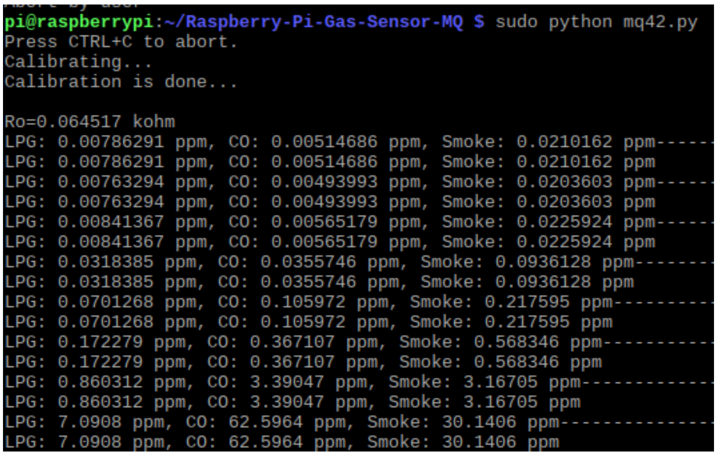


Figure 3.18: Result of Gas sensing

Analog Sensor Data Collection using MCP3008

The MCP3008 (MCP 3008,2004) is a 10-bit analog to digital converter with 8 channels (0-7)accessible over SPI. If the device is operated in differential mode, one channel is read relative to the value of a second channel. With the Raspberry Pi's SPI interfaces and its two 'Chip Select' pins available of the main GPIO connector, the ADC problem of Raspberry Pi is solved. The current value read from the device, scaled to a value between 0 and 1. Its applications include sensor interface, process control, and data acquisition.

The analog sensors like a Light-dependent resistor (LDR) and temperature detector LM35 sensors are interfaced with the raspberry pi using MCP3008 ADC converter (Figure.3.19). For this SIP and the I2C port of the raspberry pi need to be enabled, as this ADC sends the signal data through I2C interfacing. The setup is indicated in Figure.3.20.

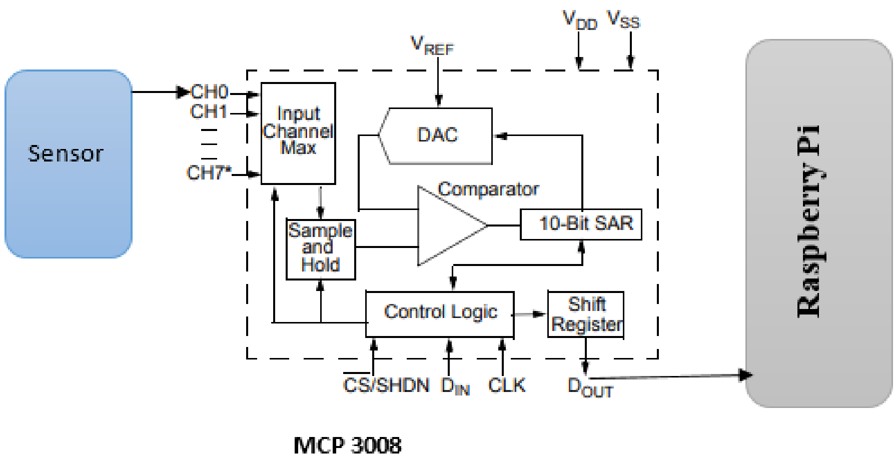


Figure 3.19: Functional diagram of ADC3008

The analog sensors like a Light-dependent resistor (LDR) and temperature detector LM35 sensors are interfaced with the raspberry pi using MCP3008 ADC converter (Figure.3.19). For this SIP and the I2C port of the raspberry pi need to be enabled, as this ADC sends the signal data through I2C interfacing. The setup is indicated in Figure.3.20.

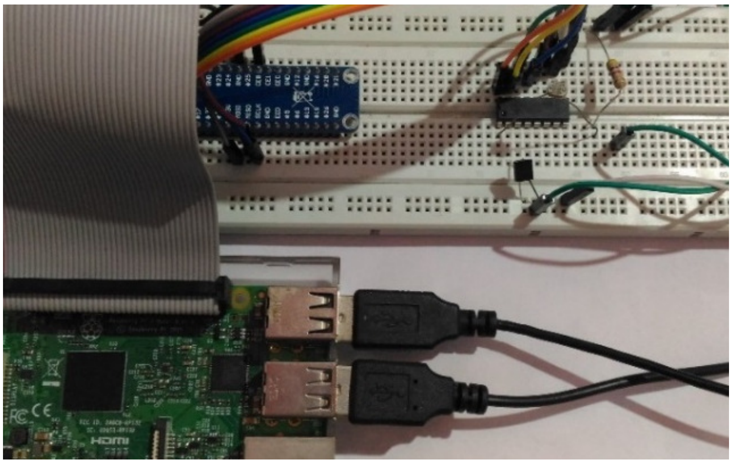


Figure 3.20: Light and Temperature measurement using ADC

The output is indicated in Figure.3.21.

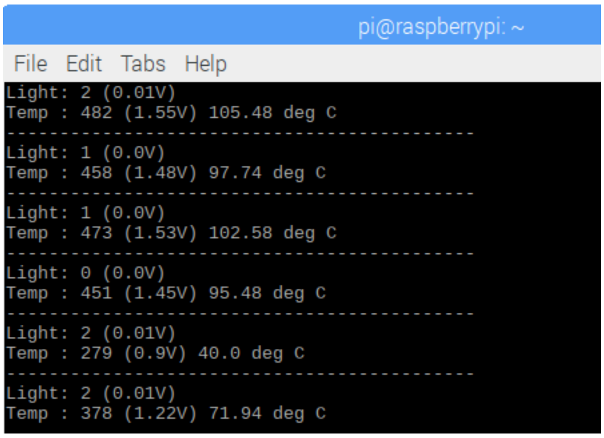


Figure 3.21: ADC output

Various parameters like temperature, pressure, light, gas, humidity are measured with the help of sensors connected to raspberry pi and python programming. This has vast applications in IoT and industrial situational monitoring.

The three possibilities of using ARM 7, Arduino microcontrollers, and Raspberry Pi processor board for safety awareness in a mining environment were studied. It can be observed that ARM 7 gives faster processing but its size is one drawback. This is especially true if it has to be embedded in the helmet. Arduino board provides advantages like the smaller size, lower cost, and easily available programming resources on the internet. It is of better choice if the circuit needed to be fixed to a safety helmet. Raspberry Pi gives net and LAN connectivity. Hence it can be used for uploading the data directly to the web. The management of data is dealt with in the next section.

3.2.3 Calibration

Some of the sensors are calibrated. Some sensors have built in calibration. For instance, the capacitive transducer is calibrated using the formula indicated below (Figure.??):

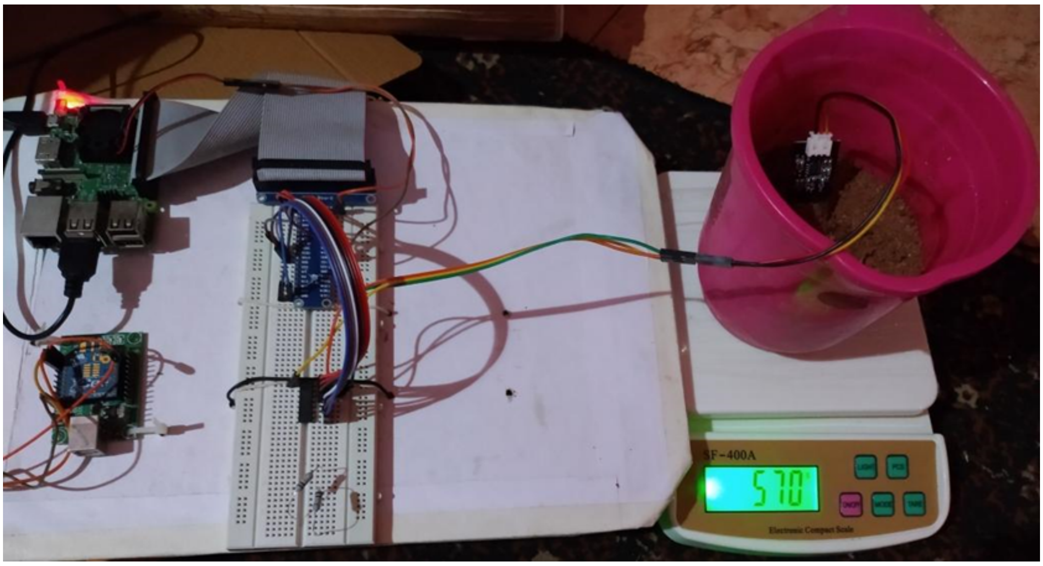


Figure 3.22: Calibration of Moisture Sensor

$$Moisture - content, \theta_v = [(m_s - m_d)/m_s] * \rho_d/\rho_s \tag{3.1}$$

Where,
m_d = mass of dry soil(400mL) = 539 g
ρ_d is bulk density of soil = 593/400 = 1.4825 g/mL
m_s = Mass of wet soil

ρ = density

Different readings were taken with the moisture sensor immersed in the mixture of soil and the different measured volume of water. The resulting calibration equation obtained is:

$$Moisture - content, \theta_v = 0.838(1/V) - 0.2847 \tag{3.2}$$

3.3 Sensor Data Collection and Management using Raspberry Pi

Sensor data collection using raspberry pi is indicated in Figure.3.23. The use of analog to digital converter MCP3008 for connecting an analog signal to raspberry pi is also studied. The study is mainly to emphasize the use of different sensors and electronic devices to monitor the parameters in a deep mining environment. The different parameters surrounding the mining environment such as temperature, humidity, barometric pressure, light, methane concentration are sensed using different types of sensors. These sensor data are analyzed using the Raspberry pi. One data is plotted as a demonstration to indicate that the sensor data can be easily plotted or analyzed using raspberry pi.

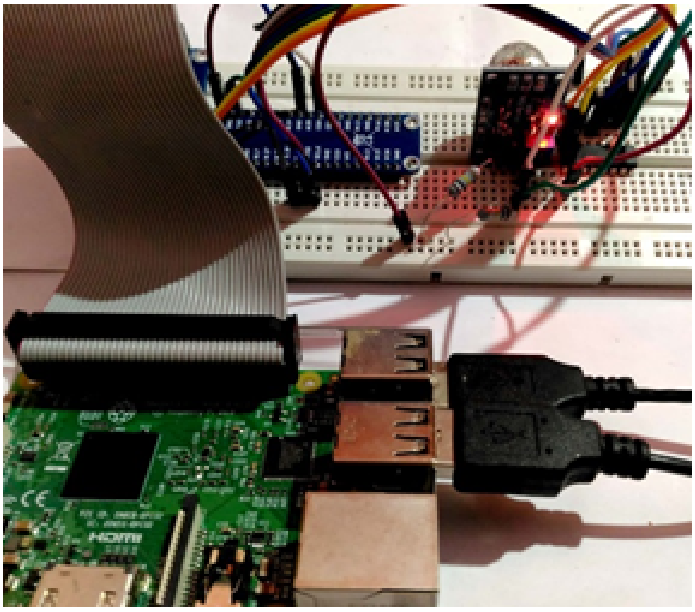


Figure 3.23: Gas sensing with MQ4

Methane gas makes the kind of power transmitted and the type of radios used challenging for WiFi technology. Also, as the equipment is not able to cover long distances, more WiFi products are needed to transmit the sensor data. The equipment should be covered with explosion-proof containers.

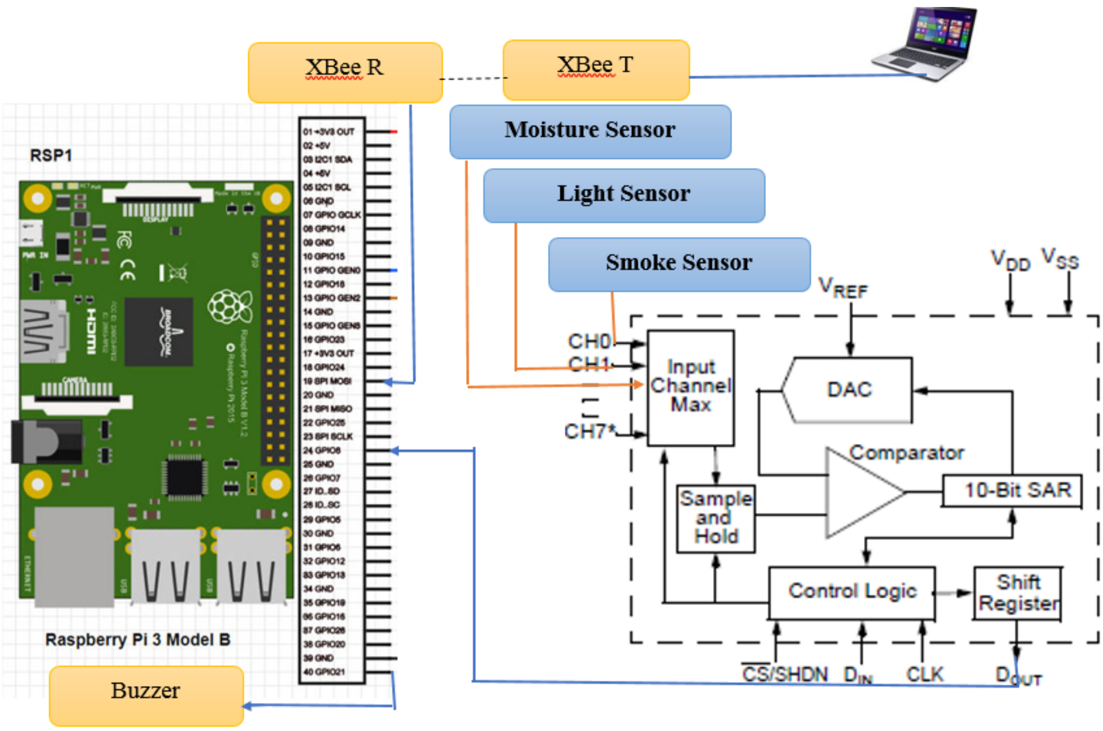


Figure 3.24: The Connection Setup

The underground atmosphere is complicated and much of the wireless transmission is lost, owing to obstructions such as rocks. The solution employing long-term evolution (LTE) technology, can transmit supervisory control and data acquisition information, as well as video and audio. The solution also has a 1 km range and comprises a variety of LTE components, including access, terminal, and portable equipment. Using LoRa communication, signal can be transmitted upto 5 kilometers.

3.3.1 Data Management and Control

Sensors are used to detect the behavior of the environment. The sensors are detecting the parameters such as temperature, CO content, etc. The sensor readings are stored in the server/controller continuously. The controller node has the threshold value for each parameter. If the sensor reading exceeds the threshold value, the controller will give the alarm signal.

One method of monitoring and control of the mining environment with wireless communication using X-bee is implemented. The measured parameter was displayed in real-time on the thingspeak website. Then the pump is controlled wirelessly using XBees connected to both Raspberry Pi and computer. This method can be extended to monitor and control the methane gas, temperature, and other parameters of the deep mining environment.

3.3.2 Data Management using ThingSpeak

The Experimental setup with sensor, raspberry pi, XBees, relay, and the pump is indicated in figure.3.25.

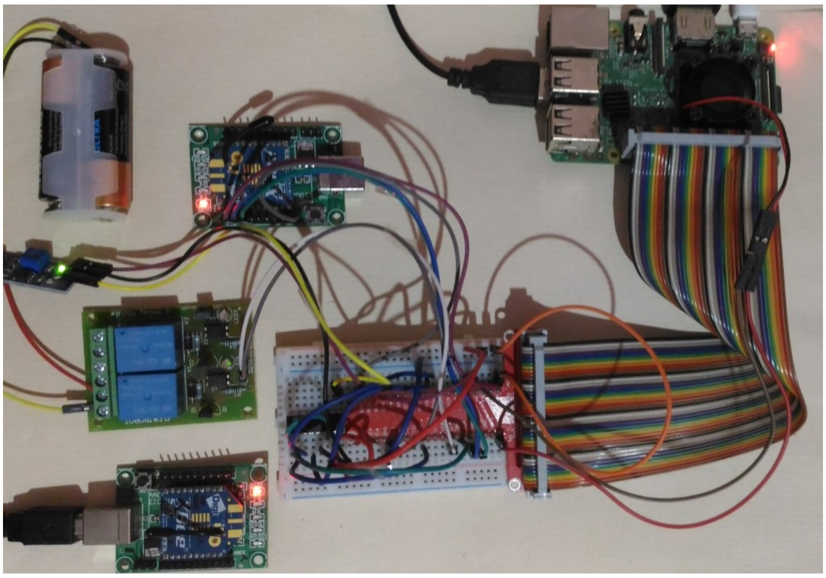


Figure 3.25: Circuit Setup

The resistive sensor is made up of two probes. The probe measures the moisture content of the soil by measuring the resistance value. When the moisture content is higher, the conductivity of soil increases leading to a change in the value of the resistance probe. When the moisture level is low, the conductivity of soil is low and correspondingly the resistance value will be lower.

Being analog sensors, both resistive and capacitive sensors need to be connected with ADC so that the digital data will be supplied to the Raspberry Pi.

Capacitive measuring eliminates corrosion of the probe and gives an improved measurement of the moisture level of the soil. Non-corrosive industrial-grade sensors are necessary for the mining environment.

3.3.3 ThingSpeak

ThingSpeak is an open-source that is helpful to collect, store and display data in the cloud. Through ThingSpeak it is possible to create public channels. Hence it is advantageous compared to some other similar platforms. The sensor data can be uploaded to the cloud with the help of raspberry pi. Simple visualizations powered by Matlab are possible on this application website. Hence it is visually attractive and is comparatively easier to analyze the collected data.

After creating a ThingSpeak account, the required number of channels is to be created depending on the number of sensors used for monitoring. The required python application programming interface (API)s and libraries need to be downloaded for uploading the measured data to the cloud. If the data needs to be analyzed separately, it can be downloaded from the ThingSpeak website in CSV or Jason format. The measured percent moisture, illumination, and CO_2 are indicated in ThingSpeak (Figure.3.27). These variations of three parameters are helping to provide the visual display of the change in parameters in real-time.

ThingSpeak uses the HTTP and MQTT protocol over the Internet or through a Local Area Network to store and retrieve data. It allows logging of sensor applications, tracing the location applications, and enables a network with its status updates. Originally launched by ioBridge in the year 2010, ThingSpeak was a service of IoT applications and now has a well-established relationship with Mathworks, Inc. It has support from the MathWorks of MATLAB software, letting users analyze and visualize data without the requirement of a MATLAB license from MathWorks.

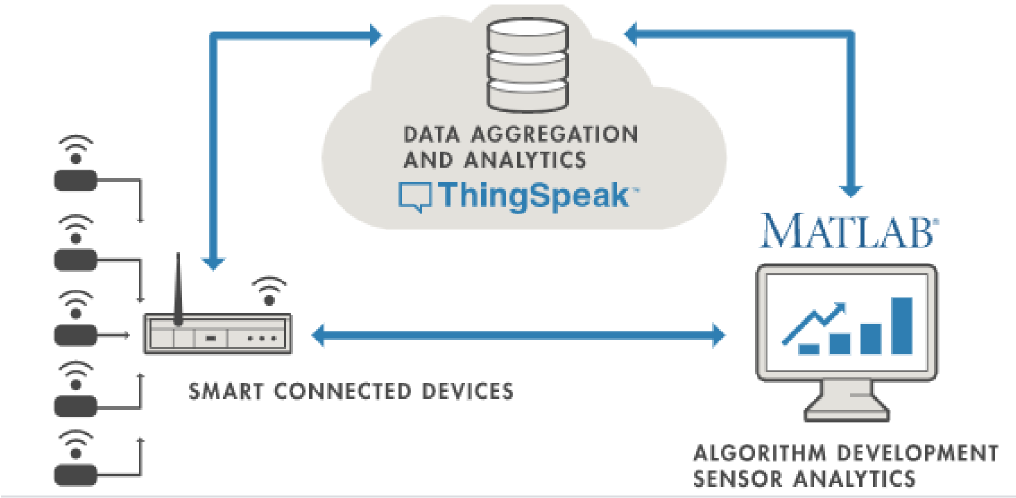


Figure 3.26: ThingSpeak

Every documentation of ThingSpeak is also included in the MathWorks' documentation site. All of the terms of service as well as the privacy policy in ThingSpeak.com are agreed in-between the user and Mathworks, Inc. ThingSpeak provides immediate visualizations of data given by the devices or equipment. Executing the MATLAB code in ThingSpeak, the online analysis could be performed and the data is processed as it comes in (Figure.3.26). ThingSpeak improves the development of beta-test of IoT systems, especially where analytics is required. One can build IoT systems without setting up servers or developing web software. For small to medium-sized IoT systems, ThingSpeak provides a good solution.

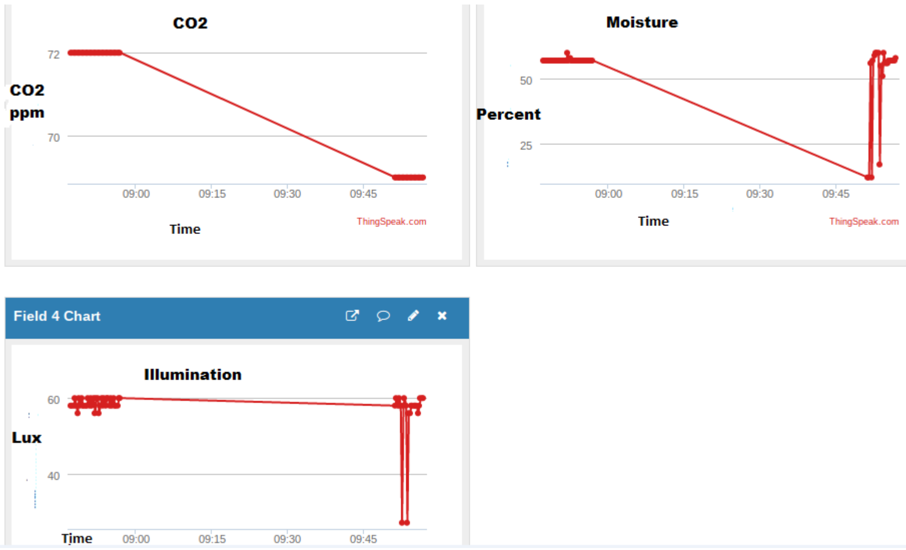


Figure 3.27: Thingspeak display

3.3.4 XBee for Data Transfer

Data transfer between the computers and controllers can be achieved by an Xbee device. It consumes low power and uses a serial port. By using a network of intermediate devices, data communication can be achieved over long distances. It becomes simple and less costly when the Xbee is used in the wireless sensor network. Wireless communication is also made possible with Xbee and a Raspberry Pi combined either using a ZigBee Dongle or Tx and Rx pins of Raspberry Pi.

IEEE 802.15.4 PHY protocol is used in XBee S2C wireless communication. Wireless communication to terminal devices is provided by XBee in any ZigBee mesh network. Other units using ZigBee technology are also well-suited to the XBee RF Module. XBee has a defined host interface, which makes programming the device simpler. The host interface API is a significant part of XBee. It is interchangeable and can manage diverse types of communication, including ZigBee, 802.15.4, and WiFi.

3.3.5 X-CTU Software

X-CTU software is used to configure the XBee. One XBee B2C is set for receiving mode and connected to the Raspberry Pi. The exact similar XBee B2C is configured for the transmitter mode. After installing explorer drivers and setting the communication port number, the window also allows indicating more specific serial features like data bits and baud rate. Then, the configuration settings of Xbee are displayed on the screen.

The two X-bees must be connected with the same baud rate as the software. One XBee is connected to Tx and Rx pins of the Raspberry Pi after installing software and setting it as a receiver. Another XBee is configured for transmitter mode and connected to the USB port of a Laptop. The correct com port and the baud rate were selected for the connected device.

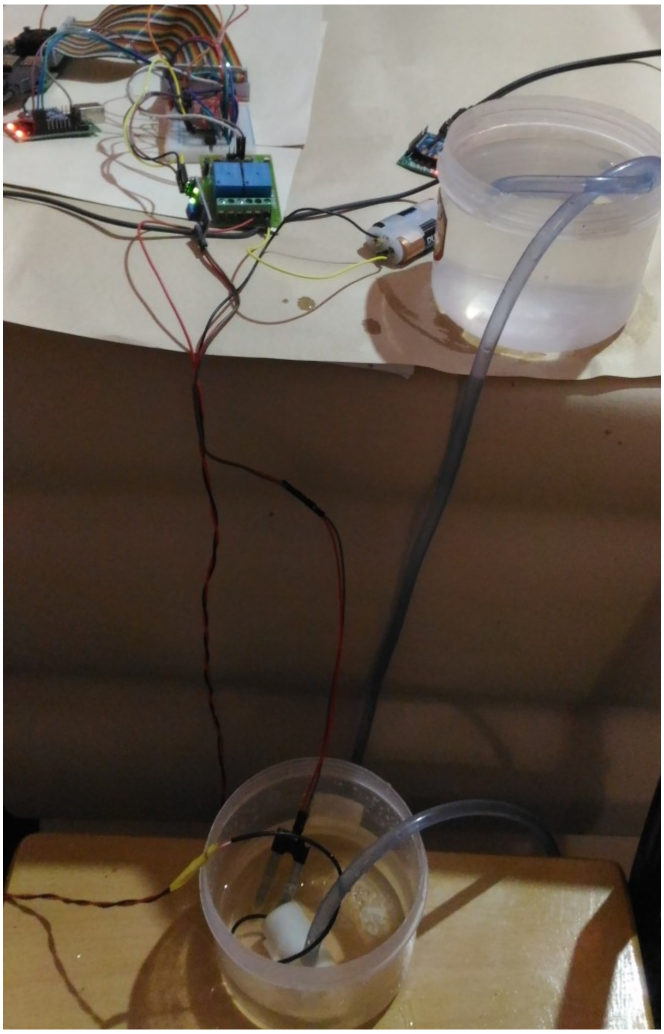


Figure 3.28: Remote Switching Setup

The control signal transferred to the Raspberry Pi will initiate the switching actions like alarming with the help of the relay. The controlling can be done from the remote computer (Figure.3.28). When letter a is pressed in a remote computer, the control action takes place. The computer and Raspberry Pi are communicating through XBees when the program is running.

The overall workflow is indicated by the flowchart indicated in Figure.3.29. The website is automatically updated. This information on the situation is used to control the mine situation remotely by Xbee communication between the control center and Raspberry Pi which will do the final control action.

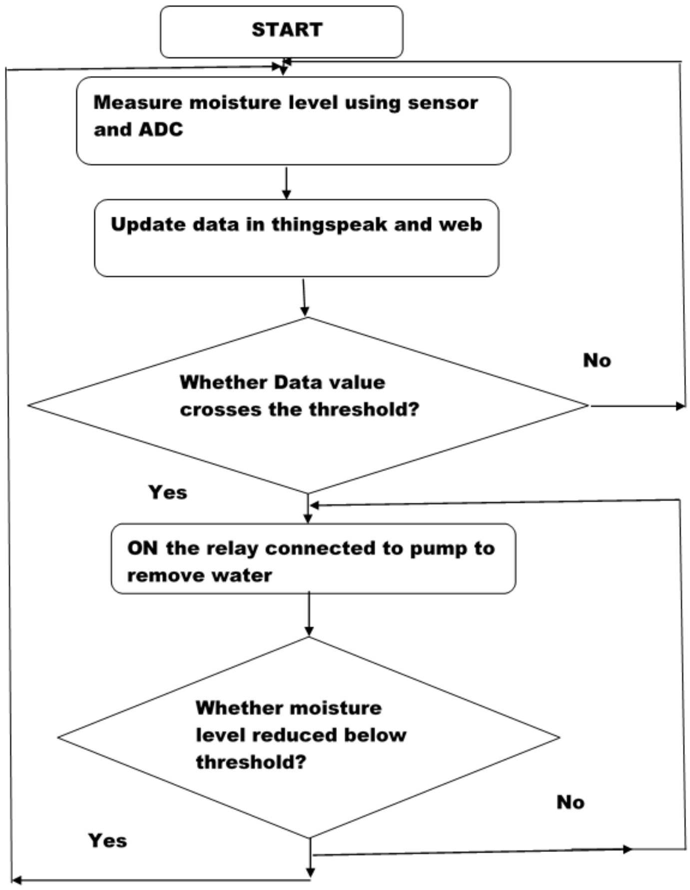


Figure 3.29: Process Flowchart

The study explored the possibility of controlling the environmental parameters remotely with the help of two Xbee modules, Raspberry Pi, and a remote computer. This method can be extended to any other IoT applications. The three sensor outputs are simultaneously obtained and the plot obtained for three sensor outputs in a ThingSpeak website.

In the second method, the sensor data is transferred from the Arduino to Raspberry Pi by wireless communication. This will also demonstrate the node and gateway of the network (Figure.3.30). functions best handled by the computing split between the end device and local network resources will be done at the edge (in flowchart writing to CSV file), while big data applications that benefit from aggregating data from everywhere and running it through analytics and machine learning algorithms running economically in hyper-scale data centers will stay in the cloud Edge (saving to CSV file and uploading in flowchart). Basic Computation is done in the raspberry pi itself.

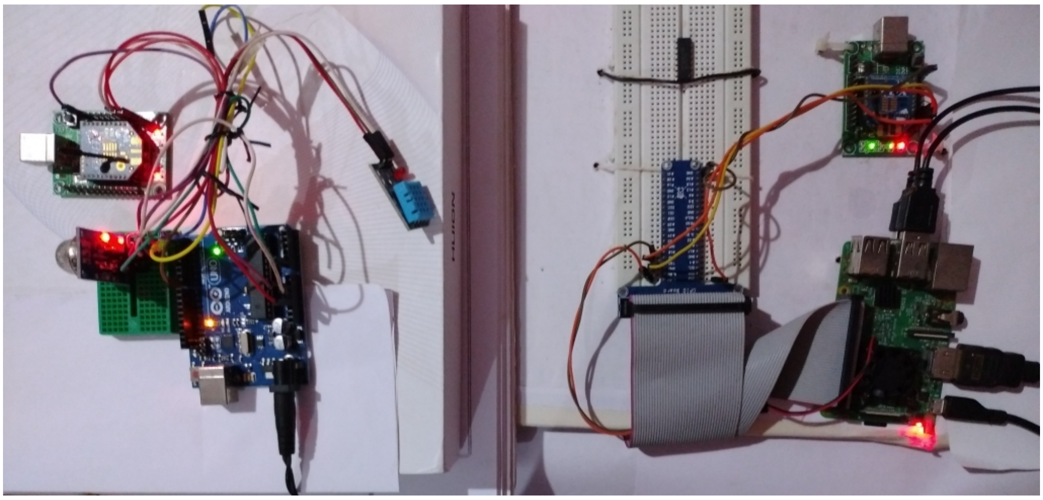


Figure 3.30: Example of Node and Gateway using Arduino and Raspberry Pi

3.3.6 The gateway Concept

Each sensor uses a standardized format for providing its parameter values (i.e., temperature, light, humidity, etc.). At the same time, supposing that a mechanism for the neighbor discovery is running; then, each sensor advertises its services. The gateway will be able to build its Neighbor Table, in which it will store data such as service name, timestamp of the last frame received from that neighbor, and connectivity statistics. That information is stored in a database and uploaded. The interactions of the gateway with sensors and/or other entities (Data Centers, local servers, etc.) are multiple and may occur depending on the particular use case. Along with the normal routing and forwarding functionality, the gateway can add further services by supporting more applications. The services have to be detected within the IoT scenarios, temporarily but in an efficient way(Figures.3.31,and 3.30).

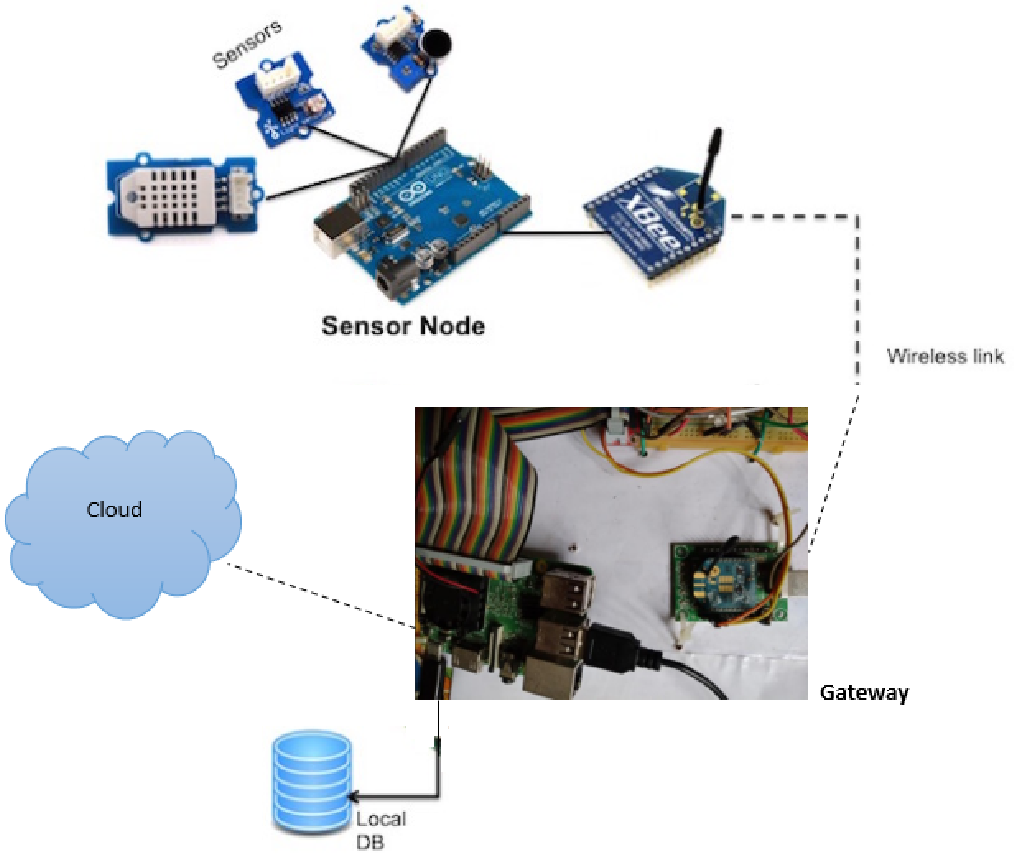


Figure 3.31: Gateway using Raspberry Pi

Line of Sight

Star topology is used for the study. star networks are connected to a centralized communication hub (sink) and the nodes cannot communicate directly with each other. The entire communication must be routed through the centralized hub. Each node is then a "client" while the central hub is the "server or sink".

Xbee uses API mode 2 for package formation and transmission. Xbee communication gave better control of raspberry pi. The line of sight issue could be tackled by increasing the number of nodes, and increasing the range of transmitters like the LoRa (Long range) node in future works. The Lora node device is being acquired. LoRa uses spread spectrum technology which eliminates the line of sight issues.

Security Aspects

MathWorks follows the appropriate privacy laws, including but not limited to EU General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). Adhering to the fair information practice principles, they comply with principles like choice, security, data integrity and limitation of purpose, onward transfer accountability, access, enforcement, recourse, and liability.
A sign-in with Mathworks is required for a user using ThingSpeak. MathWorks takes up the duty of storing any information a user provides for integrating ThingSpeak and MathWorks or any third-party services as credentials for authentication and code files. It also stores and chooses what data to send to ThingSpeak. A user can decide whether to make their data public or private. Public data is usually displayed with the MathWorks login account and links to the MathWorks account profile. Private data and apps are API keys protected that the user can reset at any time.
Users using devices, abide by basic security practices like changing default security passwords and blocking unnecessary remote access. Other steps should also include:

- Actively notifying users regarding devices that are running on outdated software or OS versions/
- Enforcing smart password management such as mandatory change of default password etc.
- Remote access to the device to be disabled unless necessary (for core functions.
- Including a strict access control policy for APIs.
- Protecting centers from attempts that compromise it.

In conclusion,two methods of monitoring and control of the environmental parameter with wireless communication using X-bee is studied. The measured parameter was displayed in real-time on the ThingSpeak website.

In the first method, the buzzer in the field is controlled by the wireless method using XBees connected to both Raspberry pi and computer. When the letter 'a' is pressed in the remote computer, the siren or indicator connected to Raspberry Pi becomes ON.

Chapter 4

Development of Situational Awareness Platform using Machine Learning Techniques

The data collected from the sensors and Raspberry Pi is already available as a separate set of data in the ThingSpeak. To analyze these data the following two techniques are sufficient namely self-organizing maps and curve-fitting regression analysis. Extreme learning machine is also used to see the improvement in accuracy of the analysis.

Just like welding and other industrial activities, pollution is a side-effect of what we do. But there is always a need to control these pollutants as these are governed by different regulations laid down by the government. No one likes dust anymore and it can affect communities and residents near the mines, so it is always required to keep dust emissions to a minimum.

Dust at mine sites comes from events like moving rock and soil, leveling, blasting, and automobiles moving on dirt roads. Most dust particles from mining are coarse dust particles. The pressure measurement using BMP180 and data generation flowchart (Figure.4.1) is given as an example for saving data in CSV format.

Table 4.1: Air Quality Satisfactory Level (Indian)

Item	Pollutant	Averaging period	Max Concentration
1	CO	8 hr and 1 hour	2 and 4 mg/m^3
2	SO2	Annual and 24 hr	50 and 80 μ g/m^3
3	PM10	Annual and 24 hr	60 and 100μ g/m^3
4	PM2.5	Annual and 24 hr	40 and 60 μ g/m^3
5	Ozone	8 hr and 1 hr	100 and 180 μ g/m^3

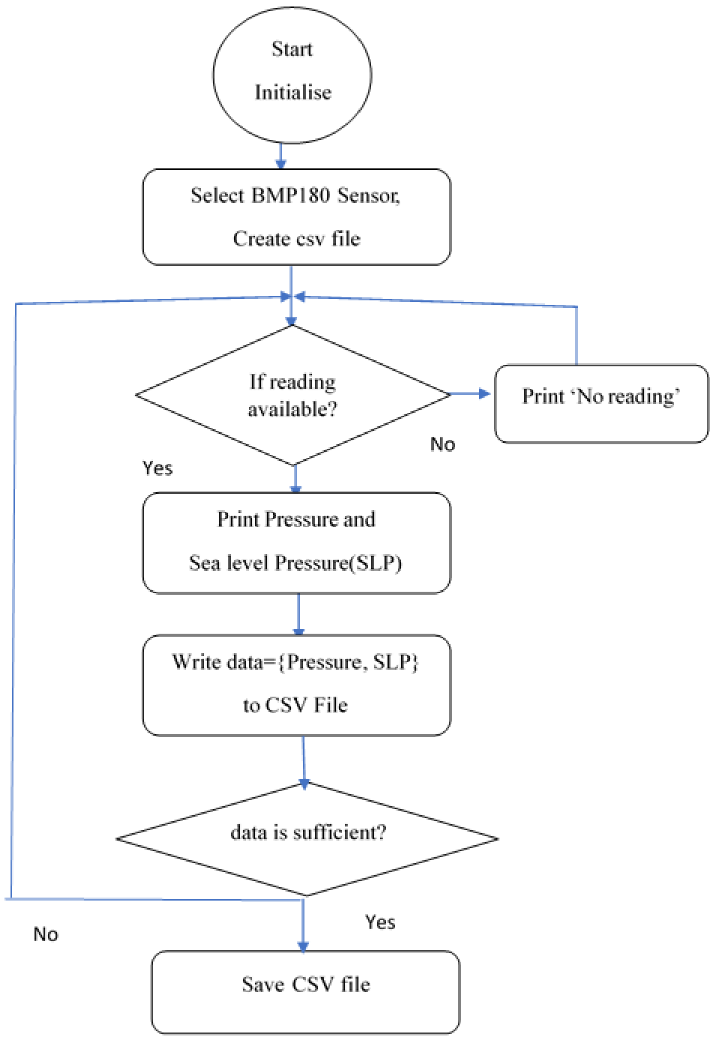


Figure 4.1: Pressure measurement flowchart

The air quality standard is indicated in table 4.1

4.1 Neural Network Curve Fitting and Regression

Curve fitting is the method of postulating the model that offers the finest fit to the particular curves in the data set. Curved correlations between variables are not as easy to fit and understand as linear relationships.

Introduction

For linear relationships, when the independent variable is advanced by one unit, the average of the dependent variable changes by a definite amount. Prediction can be a linear combination of different features as

Considering the input data values x and the target value $\hat{y}$, one can find a weight vector ω and bias term β that nearly associates data values x_i with their targets y_i.
Mathematically, we can denote the predictions y corresponding to a set of data points x using matrix notation as

For linear relationships, when the independent variable is advanced by one unit, the average of the dependent variable changes by a definite amount. Prediction can be linear combination of different features as

$$\hat{y} = w_1.x_1 + ... + w_d.x_d + \beta \tag{4.1}$$

Considering the input data values x and the target value $\hat{y}$, one can find a weight vector ω and bias term β that nearly associates data values x_i with their targets y_i.
Mathematically, we can denote the predictions y corresponding to a set of data points x using matrix notation as

$$\hat{y} = x.\omega + \beta \tag{4.2}$$

To measure the quality of the model,

$$E(y, \hat{y}) = \sum_{i}^{n} (\hat{y}_i - y_i)^2 \tag{4.3}$$

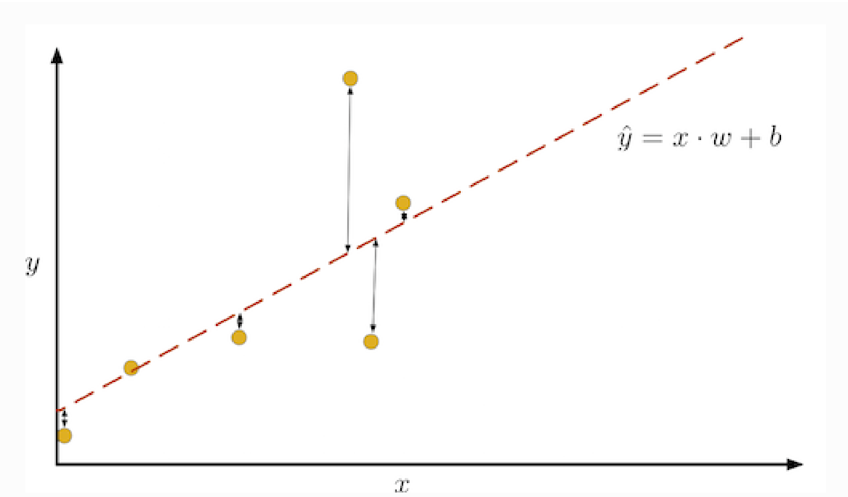


Figure 4.2: Linear Regression

For example, for the value x_i = {0.5,0.6, 0.45, 0.9,...}

$$y_1 = 0.5 * w_1 + \beta$$

$$y_2 = 0.6 * w_2 + \beta$$

$$y_3 = 0.45 * w_3 + \beta$$

$$y_4 = 0.9 * w_4 + \beta$$

For the Figure. 5.4, the graph is indicated with a value of {w, β } are {0.012, 21 } for the linear regression.

Square Loss: For a one-directional vector, one can determine the relationship between the one feature and the target value. It is also possible to determine a linear predictor and its error. The squared loss penalizes outer data points.

Manipulating the model: To reduce the error, one has to alter the model. This is achieved by choosing values of the parameters ω and β.

Neural Network

For linear models, the simplest possible useful neural network is to determine the output of the model by multiplying the input with the model's weight ω and the offset β is added.

Training the model makes it better throughout training. To find out if the goal has been reached or not, the squared distance between the prediction and the true value is calculated.

Optimizer: At each step, the gradient of the loss function concerning the weights is calculated. The parameters are updated in the direction which will reduce the loss.

Perceptron: Neural network with one neuron is called perceptron.

Epoch: An epoch refers to one cycle through the full training dataset, which means one full forward and backward pass of one dataset through a neural network.

Training loop: The number of passes to make over the dataset need to be specified.

Curved relationship: The data may have curved relationships among variables. In a curved relationship, the alteration in the dependent variable associated with a single unit change in the independent variable varies based on the position in the observation space. The curve fitting (Figure 4.2) is to obtain a mathematical representation that fits the data. Each row in the input data $\mathbf{x}$ comprises sensor data and the rows in the $\mathbf{y}$ comprise the target value. For a given point, a linear combination yields a prediction that is close to the target value. The curve fit finds the parameters with which the correlation between the function and the data is as close as possible.

The data set $\mathbf{x}$ could be the multi-dimensional input array if more than one feature is chosen and $\mathbf{y}$ matrix should be of the same length as that of matrix $\mathbf{x}$.

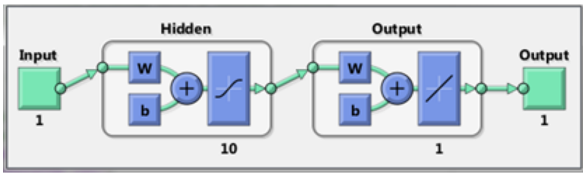


Figure 4.3: Curve fitting analysis structure

The dataset which is obtained for the air pollution, the curve fitting structure Figure.4.3 is developed for 2150 samples of carbon monoxide, 2150 samples of SO_2, 2150 samples of PM10, 1008 samples of PM2.5, and 1008 samples of ozone for the year 2019 and 2018.

Another method of clustering the gathered data will be discussed in the next section.

4.2 Self Organizing Maps for Clustering

4.2.1 Introduction

Self Organizing Map (SOM) is a clustering method that helps to categorize large datasets which are not labeled. It is a special type of unsupervised neural networks, where neurons are arranged in a single two-dimensional grid, which can take either rectangular or hexagonal shape (Figure.4.4).

Being a subset of neural networks, the SOM technique uses an unsupervised 'conqueror takes all' learning approach together with time-varying Gaussian based neighborhood apprise technique to construct a mesh of nodes to fit a data set.

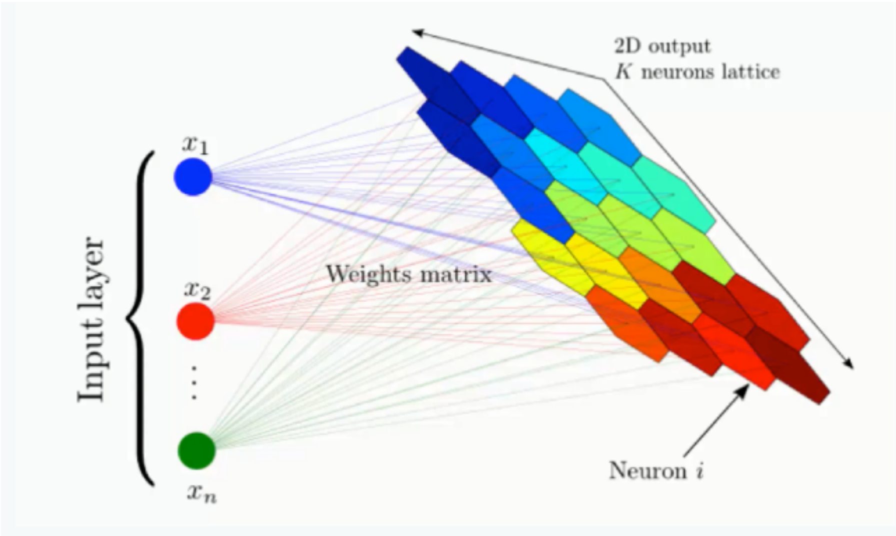


Figure 4.4: Self Organising Map

SOM creates a low-dimensional discretized depiction of the input space of the training samples, called a map, and hence a technique of dimensionality reduction and clustering. SOMs are different compared to other artificial neural networks as they apply competitive learning in contrast to error-correction learning. SOMs use a neighborhood function to maintain the topological nature of the input space.

After multiple iterations, neurons on the grid will move around the areas with a high density of data points. Hence, areas with many neurons indicate underlying clusters of input data, using a 3x3 grid so that there are 9 neurons in total. As the shape of the grid stabilizes after some iterations, the rate of change of SOM's energy reduces.
To get an idea of how many data points each neuron corresponds to, a hit map of the grid can be used. Each neuron is represented by a hexagon and the blue region within the hexagon represents the relative number of variable points that the neuron is positioned closer to.

The graphical user interface used for the data plotting and data analysis will be discussed in the next section.

From the hit map, comparing the sizes of neuron clusters, one can infer that the bigger clusters correspond to the larger group of data points.

It is possible to represent the data with multiple variables. SOM analysis needs to be repeated to check for consistency and resulting clusters should be validated.

Output $= 0$ if $\sum_i w_i, x_i \leq Threshold, i = 1, 2, 3, ...n$

Output $= 1$ if $\sum_i w_i, x_i > Threshold, i = 1, 2, 3, ...n$

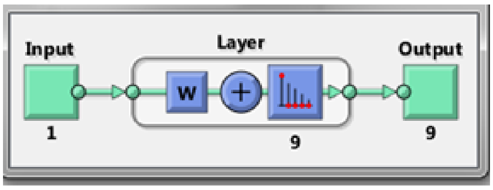


Figure 4.5: SOM method applied to CO data

In SOM, each data point in the data set recognizes itself by striving for representation. SOM mapping steps start from initializing the weight vectors. From there a sample vector is chosen arbitrarily and the map of weight vectors is explored to find which weight suits the clustering application. Each weight vector has neighboring weights that are close to it. The weight that is chosen, can become more like that randomly selected sample vector. The neighbors of that weight are also able to become more like the chosen sample vector. This allows the map to grow and form different shapes. Most generally, they form square or hexagonal shapes in 2D characteristic space. The triumphing node is commonly known as the Best Matching Unit (BMU). Afterward, the neighborhood of the BMU is estimated. The structure used for the SOM technique is indicated in Figure.4.5

The graphical user interface used for the data plotting and data analysis will be discussed in the next section.

4.3 Graphical User Interface

Matlab Guide is used to develop the graphical user interface (GUI) The different uicontrols used for the applications are

- Push buttons

- UI editable text
- UI static text
- Frames
- Axis

Axis is used to plot the graph. All of the Handle Graphics objects have properties. There are many details to manage in a GUI application.

The guide is composed of the Guide Control Panel and supporting tool, guide property editor. The GUI figure window is created using Guide and the various UI objects are fine-tuned and are automatically connected to the callback handling function when saved.

The result of creating the GUI in Guide is two files:

1. brAllplot.m which contains all of the detailed interface set-up code, and
2. brAllplot.fig which contains figure configuration.

The five parameter plots are plotted in a designed graphical user interface(GUI) and the analysis push buttons will do the SOM analysis of the three parameters. The GUI with plots are as indicated in figure 4.6.
The Carbon Monoxide(CO), Sulfur dioxide (SO_2), PM10, PM2.5, and Ozone data are analyzed for the data of Singrauli of Madhya Pradesh state and Talcher of Odisha state.

All the three plots are as indicated in figure 4.6 for the real data.

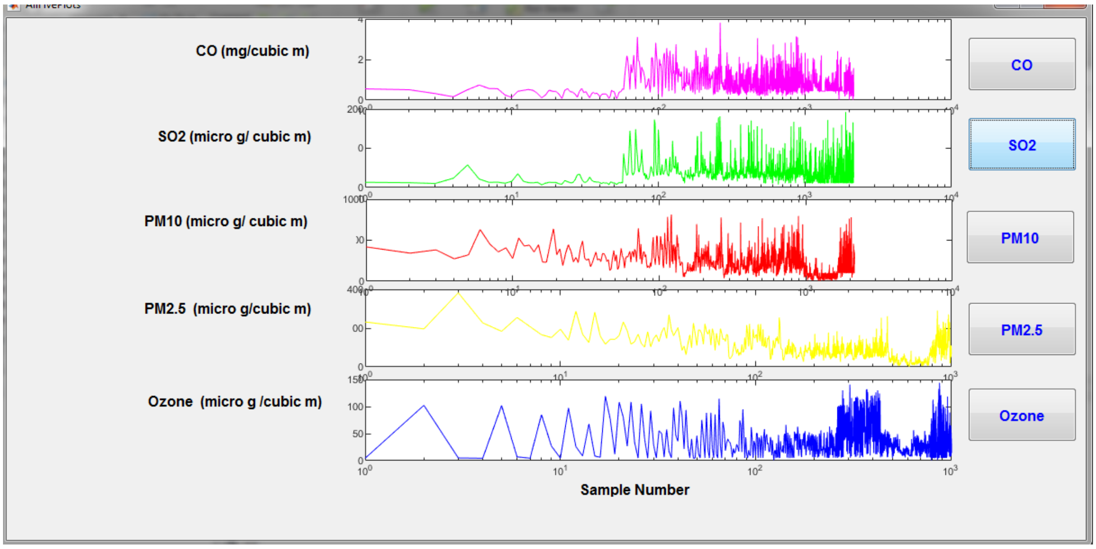


Figure 4.6: All five parameter plots

Another GUI is developed to analyze the data and to check if the data value exceeds the standards and how many times it crosses the threshold. In this GUI, the push button callback is connected to the different analysis programs. The result of this GUI is indicated in the result section.

4.4 Extreme Learning Machine (ELM) for Recognition

ELM is a type of neural network which is formed by random hidden nodes. The ELM was proposed for the single hidden layer feed-forward neural network SLFN. Given any piece-wise continuous function G(a_i,b_i, x), if continuous target function **f(x)** can be estimated by SLFNs, with changeable hidden nodes **g**, then the hidden nodes of SLFNs need not be tuned. Output function of the generalized SLFN (or ELM)(Figure4.7) is given as

$$f_L(x) = \sum_{i=1}^{L} \beta_i G(p_i, q_i, x) \tag{4.4}$$

Hidden layer output function h(x) is

$$h(x) = [G(p_1, q_1, x).....G(p_L, q_L, x)] \tag{4.5}$$

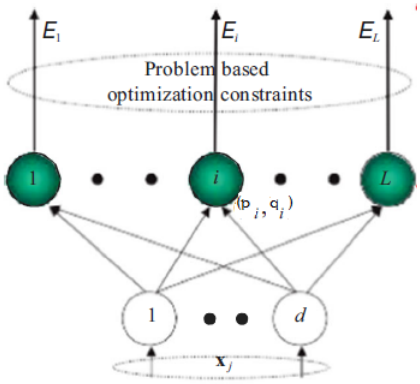


Figure 4.7: ELM

Then for any continuous target function **f(x)** and any randomly generated sequence,
$\{(p_i, q_i)_{i=1}^{L}\}$,

$$\lim_{L\to\infty} ||f(x) - f_L(x)|| = 0$$

holds with probability one if β_i is chosen to minimize
$||f(x) - f_L(x)|| = \lim_{L\to\infty} ||f(x) - f_L(x)|| = 0, \quad \forall \quad i$
The output function of hidden nodes can be sigmoid functions give by:

$$G(p_i, q_i, x) = \frac{1}{1 + e^{(-(px+q))}} \tag{4.6}$$

Suppose the training set contains n number of samples, $(Xi, Ti)_{i=1}^{n}$.
Then the ELM can approximate the **n** samples with zero error and that can be denoted as follows:

$$\sum_{j=1}^{n} ||Y_j - T_j|| = 0 \tag{4.7}$$

Where, Y is the actual output of the ELM, T is the training data-target

matrix and X is the input matrix.
For example, when the output value is 0.8 and the target value is 0.7,

0.8-0.7 = 0.1

Then the aim is to reduce this error for all the data samples.

The main feature of ELM is that the parameters of the hidden layer are randomly created and kept fixedly without any change by the iteration. An important step in ELM is to find the output weights. It is solved by reducing the training error and also the rule of the output weights. The result of all these steps is culminating in the situational awareness of the mining area which is discussed in the next section.

4.5 Situational Awareness

Web Reporter: The different sources are integrated over a graphical interface for situational awareness(Figure. 4.8).

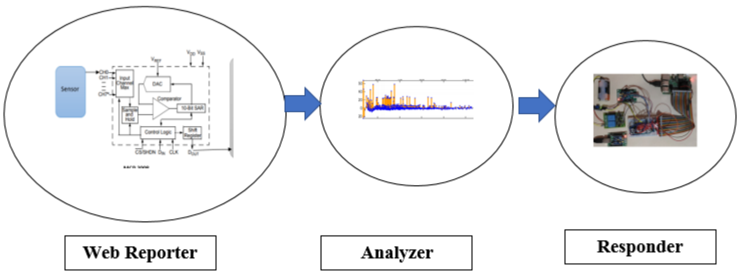


Figure 4.8: Situational Awareness

Situation Awareness for Singrauli for the Year 2019 The GUI gives output specifying that the parameter has exceeded the standard and how many times it has crossed the standard. The situation analysis performed on the Singarauli data using the developed GUI results in Figure 5.6 for the year 2019.

Analyzer: With a clearly mapped situation, comprised of surveillance, sensors, and databases, the analyzer is empowered with a correct picture of how the responders are positioned to react.

Responder: Normal response schemes connect radio-bound emergency responders back to the emergency control center to keep track of resources that can respond to an incident. The responder can find out where are the resources and their status which brings a wide-ranging view to their fingertips.

Chapter 5

Performance Evaluation of Situational Awareness Platform in Mining Industry

A)The hardware developed which was discussed in chapter 3 for the situational analysis will provide the sensors' data for different parameters in the website. The plot is for the raw data from the three sensors.

B)The software data analytics had provided the following results: The sensor data for the five parameters CO, SO2, PM10, PM2.5, and Ozone were collected from the CPCB website (CPCB,2019) making use of an advanced search method for Singarauli where open cast mine is located and Talcher where deep coal mine is located. For Singarauli, data were collected both for the years 2018 and 2019. The available data for the year 2019 was collected for Talcher. The data from Bangalore city is taken as the target data as the CO and SO2 are within the limit set by Indian standards. The Figure.5.1 indicates the variation for five parameters. The standard set by CPCB is used to compare the measured data with the standards.

The five parameters namely CO,SO_2, PM10, PM2.5, and Ozone are plotted using the designed GUI. Then parameters were analyzed using two methods for the real data collected from the repository. The SOM method gives clustering results and the curve fitting method gives the curve fitting error and regression analysis result. By this, the data clustering, as well as regression analysis, are performed and abnormalities observed. Finally, the GUI is designed for five parameter analysis which gives the number of samples that are exceeding the standards.

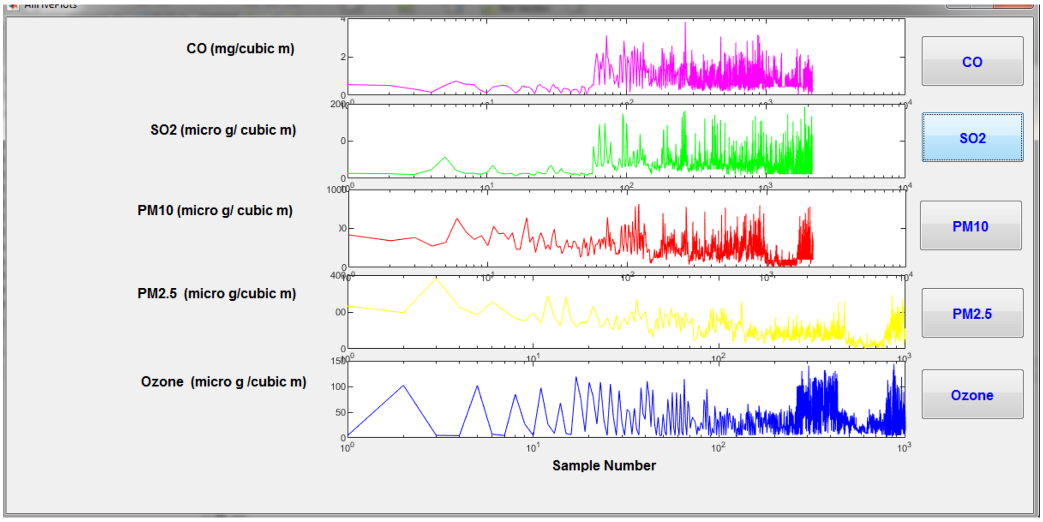


Figure 5.1: Plot of all five parameters for Singrauli

5.1 Results of NN Curve Fitting Analysis for Singrauli

The neural network curve fitting is used to check the abnormalities in the data. Using this method, the curve fitting analysis is performed on the different data.

5.1.1 CO Curve Fitting Analysis

The CO curve fitting analysis produces the plot as in Figure.5.2. From this, we can see the errors and deviation of the data from normal data like measured data for Bangalore.

The CO curve fitting analysis produces the plot as in Figure.5.2. From this we can see the errors and deviation of the data from a normal data like measured data for Bangalore.

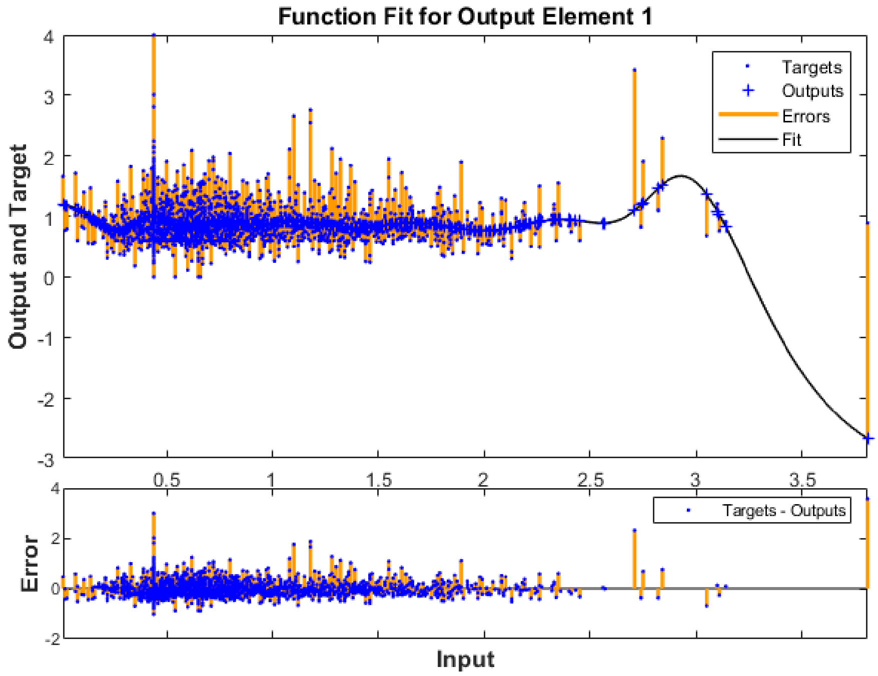


Figure 5.2: CO curve fit

5.1.2 Sulfur Dioxide Data Analysis

The SO_2 curve fit analysis produces the curve fitting plot as in Figure.5.3. From this curve, we can observe the errors and deviation of the SO_2 data.

The SO_2 regression graph is indicated in the Figure.5.4, where we can observe how the SO_2 data is deviating or fitting with a straight line. Here the data from 2018 and 2019 are compared.

5.1.3 PM10 Data Analysis

The PM10 curve fitting analysis produces the response plot as indicated by Figure.5.5. From this, we can observe the errors and deviation of the PM10 data. One can observe more error points for PM10 from this figure.

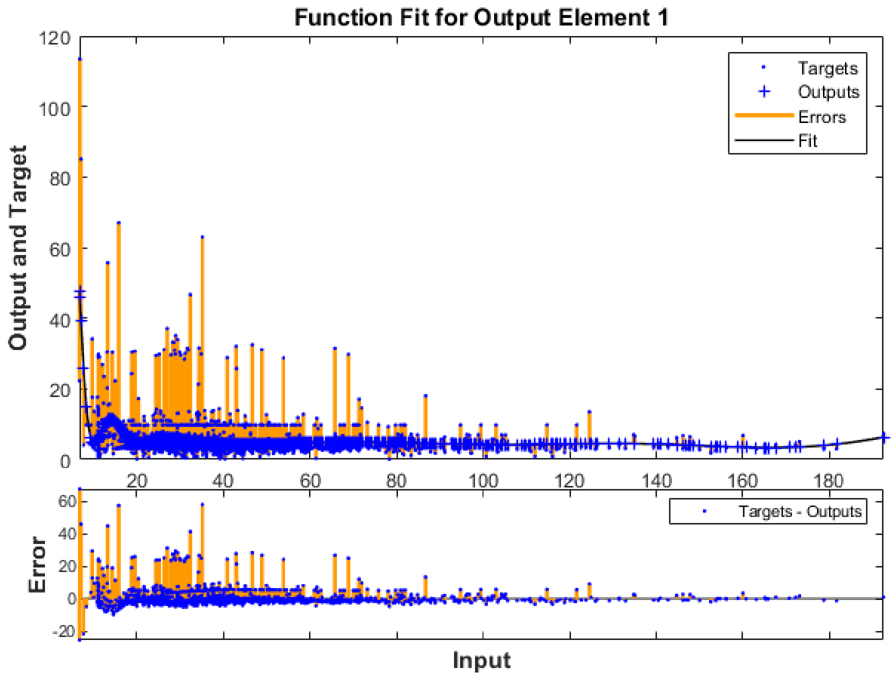


Figure 5.3: SO_2 curve fit

From the above Figures 5.2, 5.3 and 5.5, the variation in CO and Ozone are within normal variation, but error points are higher for SO_2, PM10 and PM2.5.

5.1.4 Situation Awareness for Singrauli for the Year 2019

The GUI gives output specifying that the parameter has exceeded the standard and how many times it has crossed the standard. The situation analysis performed on the Singarauli data using the developed GUI results in Figure 5.6 for the year 2019.

5.1.5 Situation Awareness for Singrauli for the Year 2018

The situation analysis performed on the Singarauli data for the year 2018 is indicated in Figure 5.7.

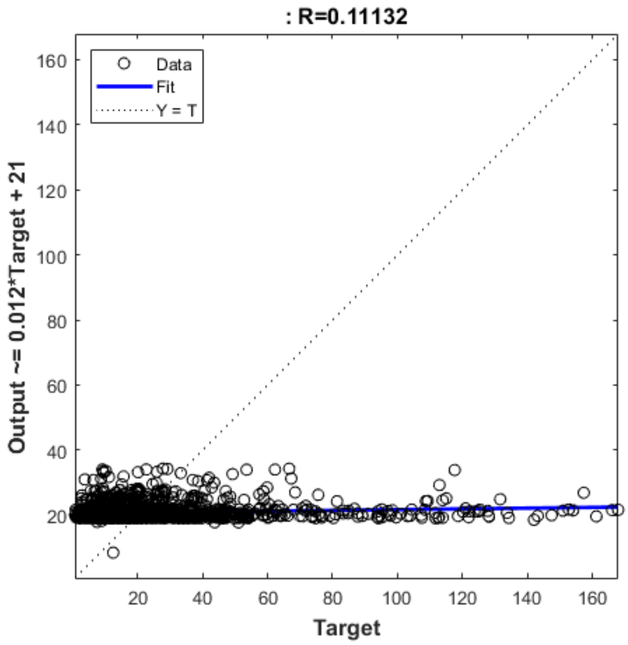


Figure 5.4: SO_2 regression

5.1.6 Result Table for Singrauli

The comparison between the 2018 and 2019 situation for Singrauli is indicated in table.5.1. There is an increase in SO_2 level from the year 2018 to the year 2019.

5.2 Results of SOM Analysis for Singrauli

5.2.1 CO Data Analysis by SOM

The CO data analysis for clustering using SOM produces the following results for hits (Figure 5.8). The network has clustered the data depending on the number of outputs chosen which is 9. In this case, 7 clusters have hits above 100.

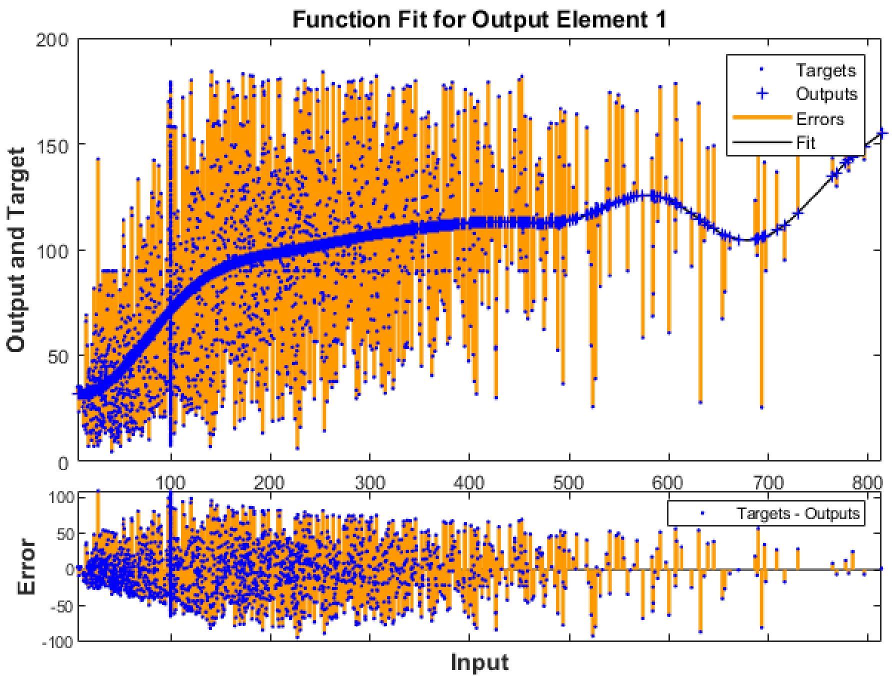


Figure 5.5: PM10 Curve fitting

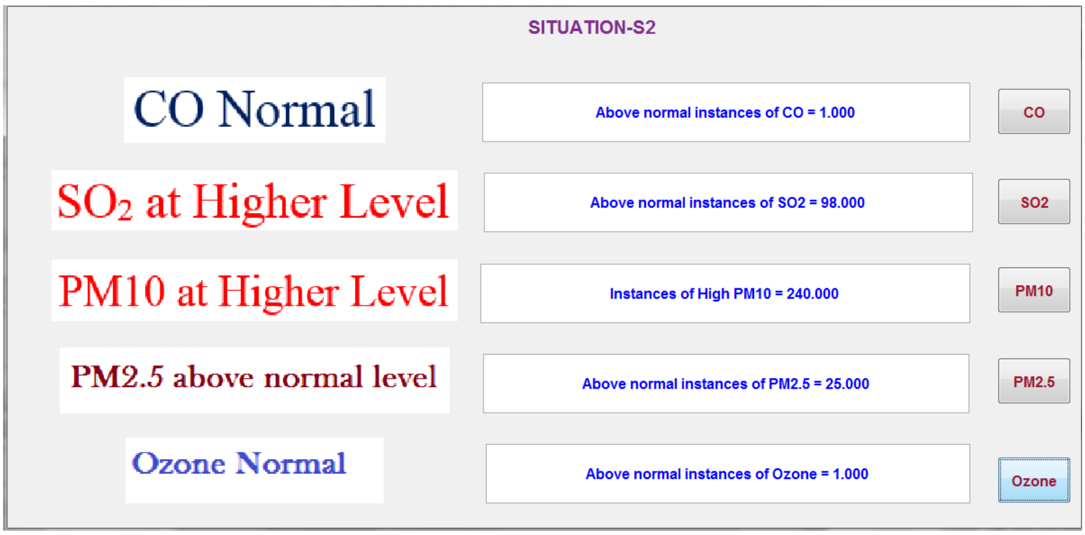


Figure 5.6: Situation awareness 2019

5.2.2 Sulfur Dioxide Data Analysis by SOM

The SOM hit map accuracy increases as the dimension number and number of iterations increased. By increasing the matrix to 4 x 4, the SOM

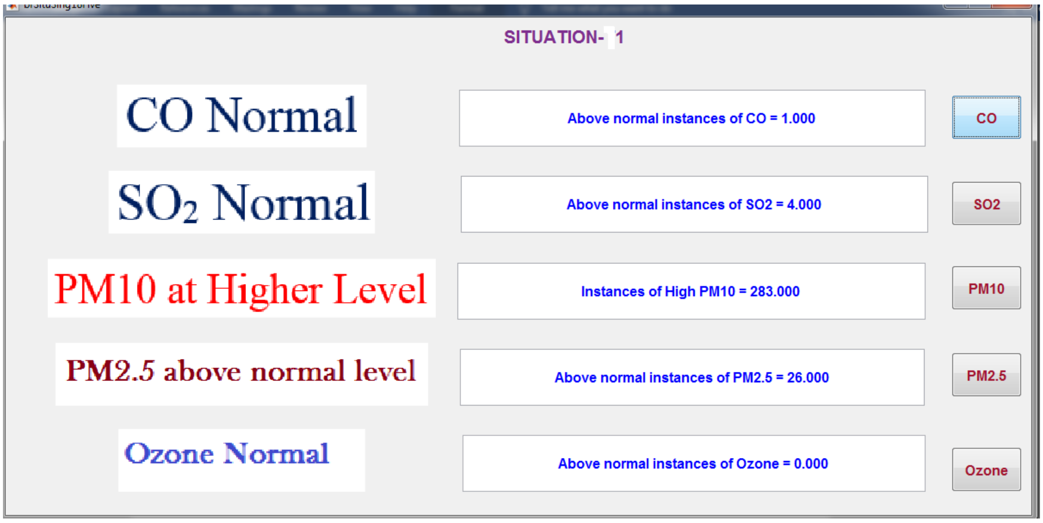


Figure 5.7: Situation awareness 2018

Table 5.1: Air quality as measured for Singrauli

	Year	2018	2019
1	CO Exceedance	1	1
2	SO_2 exceedance	4	98
3	PM10 exceedance	283	240
4	PM2.5 exceedance	26	25
5	Ozone exceedance	0	1

produces 16 clusters. The Sulfur Dioxide (SO_2) data analysis for clustering using SOM produces the following results for hits (Figure.5.9). The network has clustered the data depending on the number of outputs chosen which is 16 in this case. The number of clusters having hits above 100 are 9.

5.2.3 PM10 Data Analysis by SOM

The PM10 data analysis clustered the data depending on the number of outputs chosen. In this case, 9 clusters are obtained. It has 7 clusters with more than 100 sample hits.

The SOM analysis provides a visual display to the responder so that where are the major data clusters are located.

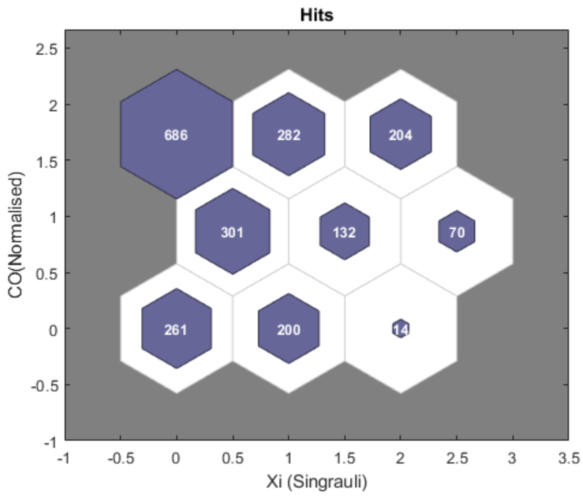


Figure 5.8: CO hit plot

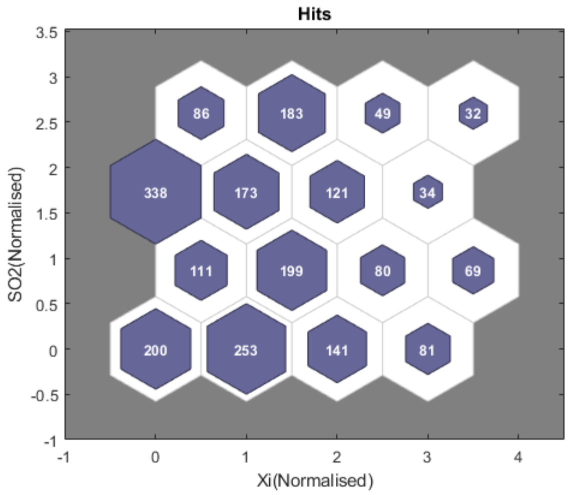


Figure 5.9: SO_2 hit plot

5.3 Results of NN Curve Fitting Analysis for Talcher

The sensor data for Talcher, where deep coal mine is located is plotted in Figure 5.10

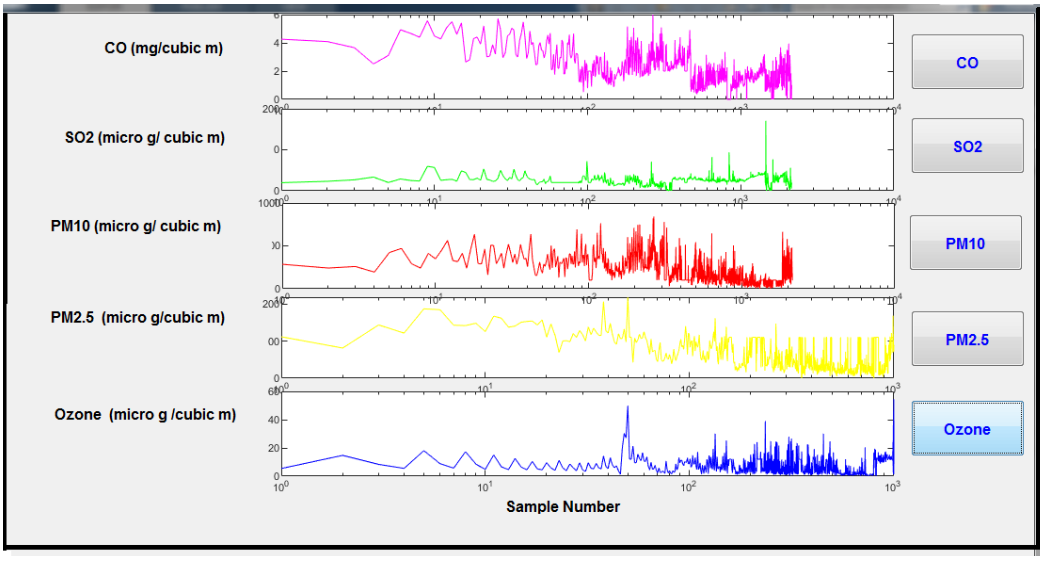


Figure 5.10: Plots of parameters for Talcher

5.3.1 CO NN Curve Fitting Analysis

Analysis of CO for Talcher with curve fitting is as in figure 5.11.

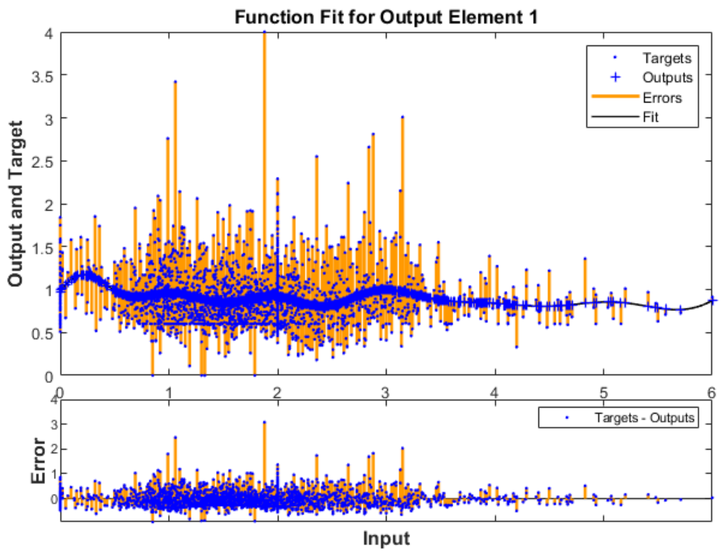


Figure 5.11: CO analysis for Talcher

From the above analysis,5.11, the variation in CO as well as SO_2 are within normal variation, but error points are higher for PM10 and PM2.5.

5.3.2 Situation Awareness for Talcher

The situation analysis GUI is indicated in Figure 5.12

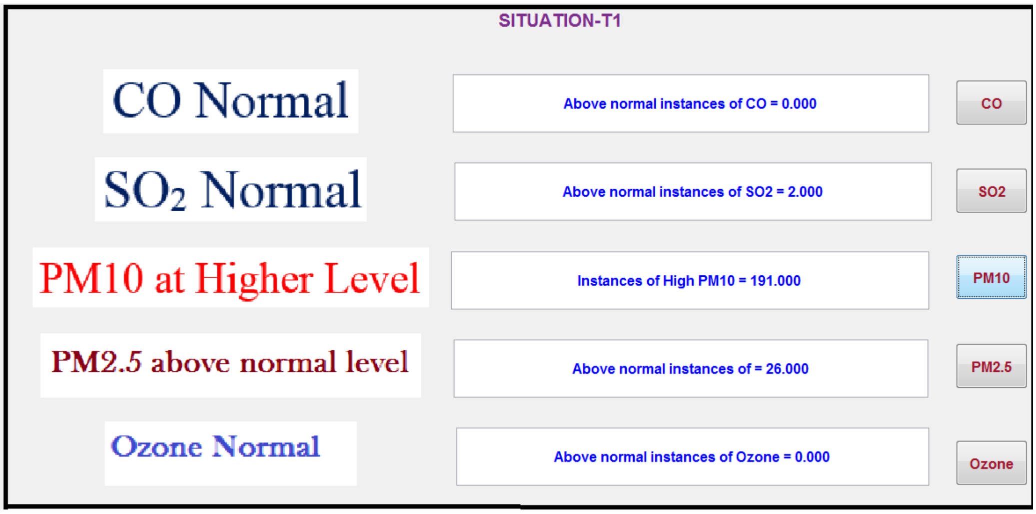


Figure 5.12: Situation Awareness Platform for Talcher

5.3.3 Result Table for Talcher

The data analysis for Talcher where deep coal mine is located is as indicated in table 5.2

Table 5.2: Air quality as measured for Talcher

	Year	2019
1	CO Exceedance	0
2	SO_2 exceedance	2
3	PM10 exceedance	191
4	PM2.5 exceedance	26
5	Ozone exceedance	0

5.4 Results of SOM Analysis for Talcher

5.4.1 CO Analysis by SOM

The SOM analysis for Talcher for CO analysis is as indicated in Figure. 5.13.The network has clustered the data depending on the number of outputs chosen which is 9. In this case 7 clusters have hits above 100.

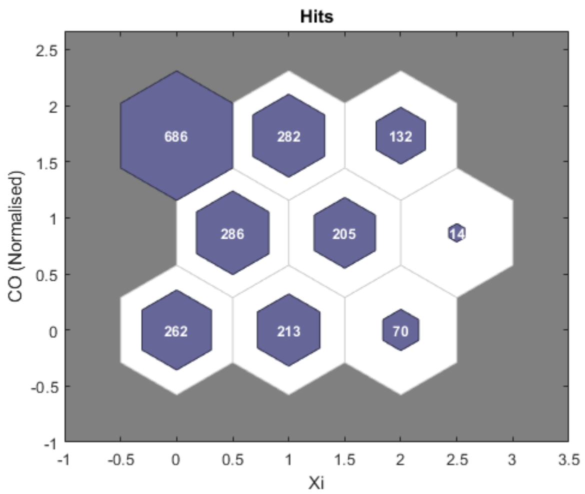


Figure 5.13: CO analysis for Talcher

5.4.2 Sulfur Dioxide and PM10 Analysis by SOM

The SOM analysis for Talcher for SO_2 analysis results in 6 clusters having hits above 100.

The SOM analysis for Talcher for PM10 analysis results in 6 clusters having hits above 100. The above three cases are taken as examples of SOM clustering method for Talcher.

5.5 Extreme Learning Machine

The extreme learning machine is suitable for mining data when there is already category-wise data is available. As a classifier, it will provide good results as indicated in Figure.5.14 for the measured data from sensor compared to other methods.

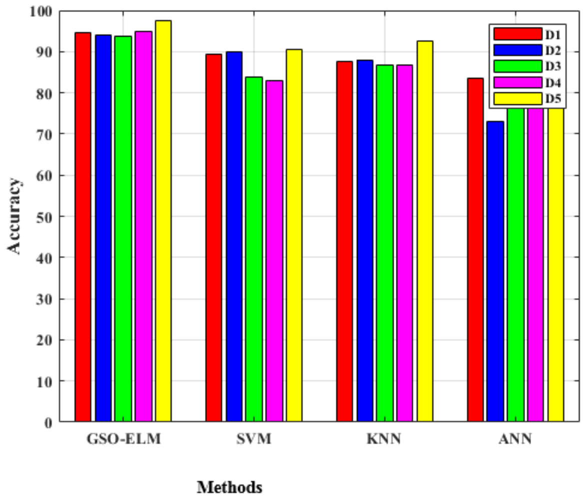


Figure 5.14: ELM comparison

Chapter 6

Conclusive Remarks and Scope for Future Research

- Different hardware implementations for situational awareness are developed. These include the circuit using Arduino Uno microcontroller, a circuit using ARM 7 microcontroller, and the Raspberry Pi single-board computer-based circuits.
- Wireless communication and control using XBee are performed.
- The neural network-based data analytics is used to perform the analysis on the environmental parameters. The different techniques like SOM and Regression methods are used to perform the analysis on the environmental parameters like CO, SO_2, PM10, PM2.5, and Ozone.
- The Graphical user interface is developed. A GUI developed analyses the data vector and gives the situation as output by comparing it with the standards. The real data from the CPCB website is used to analyze the situation of the air quality. This GUI can be used to analyze any other parameters related to mining.
- From the data analytics used, there is the pollution of both SO_2 and PM surrounding the Singarauli area. One could observe that there is a worsening of SO_2 pollution level from the year 2018 to 2019 in the

Singarauli area. There is no much difference in pollution levels of CO, PM2.5, and Ozone from the year 2018 to the year 2019.

- As Talcher has a deep coal mine, the SO_2 level is within permissible limits outside the mine, although the PM10 and PM2.5 levels are high.

6.1 Future Scope

- Landscape and satellite image data can be analyzed so that the landslide and other disasters could be predicted.
- Gateway hardware like LoRa Gateway could be used to upload many sensors' data to the cloud over long distance. The security issue can be researched upon.
- New data analysis techniques can be used for the analysis as the faster processors are available to use neural network analysis.

Papers Published

- Ramesh B and Vittal K P,(2017). "An ontology aided GSO optimized extreme learning for situation recognition in coal mining environment", *Journal of Advanced research in dynamical and control systems*, Vol.9,sp-14, pp.1569-1590.

- Ramesh B and Vittal K P(2018), "wireless sensor networks for situation awareness in coal mining environment", *Journal of computational and theoretical Nanoscience*, Vol.15,sp-14, pp.2242-2244.

- Ramesh B and Vittal K P (2019),"Situation awareness of deep mining environment using raspberry pi", *Journal of computational and theoretical Nanoscience*, Vol 6, pp.2604-2608.

Conferences:

- Ramesh B, and Vittal, K.P(2015), "Upgrading Substation Relays to Digital Reclosers and their Coordination with Sectionalizers". Proceedings of 4th IRF International Conference 85-89.

- Ramesh B, and Vittal, K.P(2018), "wireless sensor networks for situation awareness in coal mining environment", ICRTET, June 2018, Vemana Institute of Technology, Bangalore.

- Ramesh B and Vittal K P, (2019)."Wireless monitoring and control of deep mining environment using ThingSpeak and Xbee",ICIDCA, Springer (Accepted).

Appendices

Appendix A

Data-sheet Links

https://www.mouser.com/pdfdocs/Arduino

http://www.keil.com/dd/docs/datashts/philips/lpc2141-42-44-46-48.pdf

https://www.raspberrypi.org/products/raspberry-pi-3-model-b

https://www.mouser.in/manufacturer/microchip/MCP3008

https://www.bosch-sensortec.com/BMP180

http://www.parallax.com/downloads/MQ-4

http://www.parallax.com/downloads/MQ-7

http://www.datasheetspdf.com/pdf-file/785590/D-Robotics/DHT11

Appendix B

Programs

MATLAB Programmes

brSingAir3.m

```
function varargout = brSingAir3(varargin)
gui_Singleton = 1;
gui_State = struct('gui_Name',       mfilename, ...
                   'gui_Singleton',  gui_Singleton, ...
                   'gui_OpeningFcn', @brSingAir3_OpeningFcn, ...
                   'gui_OutputFcn',  @brSingAir3_OutputFcn, ...
                   'gui_LayoutFcn',  [] , ...
                   'gui_Callback',   []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
% End initialization code


% --- Executes just before brBangAir3 is made visible.
function brSingAir3_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args,

% varargin   command line arguments to brBangAir3

handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% uiwait(handles.figure1);

 function varargout = brBangAir3_OutputFcn(hObject, eventdata, handles)

% Get default command line output from handles structure
varargout{1} = handles.output;


% --- Executes on button press in COpb.
function COpb_Callback(hObject, eventdata, handles)
t=(1:1:3880)
CO=load('dataBangCOn.csv')
```

```
semilogx(handles.axes1,t,CO,'m')
y1=0
for t= 1:3800
    while (CO>8)
    y1=y1+1
end
end
y1
while (y1>10)
    [x,c]=imread('CODanger.png','png')
    x=imread('CODanger','png')
   plot(handles.axes1, image(x))
end
brBangCOSOM1
% --- Executes on button press in SO2pb.
function SO2pb_Callback(hObject, eventdata, handles)
% hObject    handle to SO2pb
t=(1:1:3880)
SO2=load('dataBangSO2n.csv')
semilogx(handles.axes2,t,SO2,'g')
brBangSO2SOM1
% --- Executes on button press in Humpb.
function Humpb_Callback(hObject, eventdata, handles)
% hObject    handle to Humpb
% handles    structure with handles and user data
t=(1:1:2300)
gaseP=load('dataBangHu.csv')
semilogx(handles.axes3,t,gaseP,'r')
brBangHumSOM1
```

situation.m

```
function varargout = SituationModif(varargin)

gui_Singleton = 1;
gui_State = struct('gui_Name',       mfilename, ...
                   'gui_Singleton',  gui_Singleton, ...
                   'gui_OpeningFcn', @SituationModif_OpeningFcn, ...
                   'gui_OutputFcn',  @SituationModif_OutputFcn, ...
                   'gui_LayoutFcn',  [] , ...
                   'gui_Callback',   []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
```

```
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
% End initialization code


% --- Executes just before SituationModif is made visible.
function SituationModif_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args,

handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% uiwait(handles.figure1);

function varargout = SituationModif_OutputFcn(hObject, eventdata, handles)

% Get default command line output from handles structure
varargout{1} = handles.output;


% --- Executes on button press in COpb.
function COpb_Callback(hObject, eventdata, handles)
brBangCOFit
if(count1>10)

myImage = imread('CODanger2.png');
axes(handles.axes1);
imshow(myImage);
else

myImage = imread('CONormal2.png');
axes(handles.axes1);
imshow(myImage);
% axes(handles.axes1);
% print('Instances above standard is',y1)
drawnow
end

string1 = sprintf('Above normal instances of CO = %.3f', count1)
set(handles.edit1, 'String', string1)

% --- Executes on button press in SO2pb.
```

```
function SO2pb_Callback(hObject, eventdata, handles)
% hObject    handle to SO2pb
brBangSO2Fit
% a1=0
if(count2>5)
    myImage2 = imread('So2danger.png')
    axes(handles.axes2);
imshow(myImage2);
else

myImage2 = imread('So2normal.png')
axes(handles.axes2);
imshow(myImage2);

end
% end
string2 = sprintf('Above normal instances of SO2 = %.3f', count2)
set(handles.SO2ed, 'String', string2)

% --- Executes on button press in Humpb.
function Humpb_Callback(hObject, eventdata, handles)
% hObject    handle to Humpb (see GCBO)

brSingPMFit

if(count3>8)

myImage3 = imread('PM10.png');
axes(handles.axes3);
imshow(myImage3);
else

myImage3 = imread('PM10.png');
axes(handles.axes3);
imshow(myImage3);
% axes(handles.axes1);
% print('Instances above standard is',y1)
drawnow
end

string3 = sprintf('Instances of High PM10 = %.3f', count3)
set(handles.Humed, 'String', string3)


function edit1_Callback(hObject, eventdata, handles)
```

```
% --- Executes during object creation, after setting all properties.
function edit1_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit1 (see GCBO)
if ispc && isequal(get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end



function SO2ed_Callback(hObject, eventdata, handles)
% hObject    handle to SO2ed (see GCBO)

% --- Executes during object creation, after setting all properties.
function SO2ed_CreateFcn(hObject, eventdata, handles)
% hObject    handle to SO2ed
if ispc && isequal(get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end



function Humed_Callback(hObject, eventdata, handles)

% --- Executes during object creation, after setting all properties.
function Humed_CreateFcn(hObject, eventdata, handles)
% hObject    handle to Humed

if ispc && isequal(get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end
```

brSingCOSOM1.m

```
%   hum3_3 - input data.
CO=load('dataSingCO.csv')
x = CO';

% Create a Self-Organizing Map
dimension1 = 4;
dimension2 = 4;
net = selforgmap([dimension1 dimension2]);

% Choose Plot Functions
net.plotFcns = {'plotsomtop','plotsomnc','plotsomnd', ...
    'plotsomplanes', 'plotsomhits', 'plotsompos'};
```

```
% Train the Network
[net,tr] = train(net,x);

% Test the Network
y = net(x);

% View the Network
view(net)

% Plots
%figure, plotsomtop(net)
%figure, plotsomnc(net)
%figure, plotsomnd(net)
%figure, plotsomplanes(net)
figure, plotsomhits(net,x)
%figure, plotsompos(net,x)
%plotperform(net,x)

% Deployment
if (false)
   genFunction(net,'myNeuralNetworkFunctionHSOM');
   y = myNeuralNetworkFunctionHSOM(x);
end
if (false)
   genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
   y = myNeuralNetworkFunctionHSOM(x);
end
if (false)
   % Simulink Coder tools.
   gensim(net);
end
```

brSingSO2SOM1.m

```
% This script assumes these variables are defined:
%   hum3_3 - input data.
SO2=load('dataSingSO2.csv')
x = SO2';
% Create a Self-Organizing Map
dimension1 = 3;
dimension2 = 3;
net = selforgmap([dimension1 dimension2]);

% Choose Plot Functions
```

```
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotsomtop','plotsomnc','plotsomnd', ...
    'plotsomplanes', 'plotsomhits', 'plotsompos'};

% Train the Network
[net,tr] = train(net,x);

% Test the Network
y = net(x);

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotsomtop(net)
%figure, plotsomnc(net)
%figure, plotsomnd(net)
%figure, plotsomplanes(net)
figure, plotsomhits(net,x)
%figure, plotsompos(net,x)

% Deployment
if (false)
    genFunction(net,'myNeuralNetworkFunctionHSOM');
    y = myNeuralNetworkFunctionHSOM(x);
end
if (false)
    genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunctionHSOM(x);
end
if (false)
    % Generate a Simulink diagram for simulation or deployment with.
    % Simulink Coder tools.
    gensim(net);
end
```

brSingPMSOM1.m

```
% This script assumes these variables are defined:
%
%   hum3_3 - input data.
hum3=load('dataBangHu.csv')
x = hum3';
```

```
% Create a Self-Organizing Map
dimension1 = 6;
dimension2 = 6;
net = selforgmap([dimension1 dimension2]);

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotsomtop','plotsomnc','plotsomnd', ...
    'plotsomplanes', 'plotsomhits', 'plotsompos'};

% Train the Network
[net,tr] = train(net,x);

% Test the Network
y = net(x);

% View the Network
view(net)

% Plots
%figure, plotsomtop(net)
%figure, plotsomnc(net)
%figure, plotsomnd(net)
%figure, plotsomplanes(net)
figure, plotsomhits(net,x)
%figure, plotsompos(net,x)

% Deployment
if (false)
     genFunction(net,'myNeuralNetworkFunctionHSOM');
    y = myNeuralNetworkFunctionHSOM(x);
end
if (false)
    genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunctionHSOM(x);
end
if (false)
    % Generate a Simulink diagram for simulation or deployment with.
    % Simulink Coder tools.
    gensim(net);
end
```

----

brSingCOFit.m

```
dataBangCOn=load('dataSingCOn.csv')
```

```
dataBangCOm=load('dataBangCOm.csv')
x = dataBangCOn';
t = dataBangCOm';

% Choose a Training Function
% Create a Fitting Network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
global count1
count1 =0
for t1= 1:1:3880
e1(t1)=abs(e(t1))
if (e1(t1)>3)
    count1=count1+1
else
   count1=count1+0
end
end
if (count1>4)
disp('too many deviations')
```

```
else
disp('Normal situation')
end
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)

% Deployment
if (false)

   genFunction(net,'myNeuralNetworkFunctionSO2');
   y = myNeuralNetworkFunction(x);
end
if (false)
   genFunction(net,'myNeuralNetworkFunctionSO2','MatrixOnly','yes');
   y = myNeuralNetworkFunctionSO2(x);
end
if (false)
   % Generate a Simulink diagram for simulation or deployment with.
   % Simulink Coder tools.
   gensim(net);
end
```

----

brSingSO2Fit.m

```
%   dataBangSO2n - input data.
%   dataBangSO2ns - target data.
dataBangSO2n=load('dataSingSO2n.csv')
dataBangSO2ns=load('dataBangSO2ns.csv')
```

```
x = dataSingSO2n';
t = dataBangSO2ns';

% Choose a Training Function

% Create a Fitting Network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y)
global count2
count2 =0
for t1= 1:1:3880
e1(t1)=abs(e(t1))
if (e1(t1)>.03)
    count2=count2+1
else
   count2=count2+0
end
end
if (count2>10)
```

```
disp('too many deviations')
else
disp('Normal situation')
end
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)

% Deployment
if (false)
   % Generate MATLAB function
   genFunction(net,'myNeuralNetworkFunctionSO2');
   y = myNeuralNetworkFunction(x);
end
if (false)
   % Generate a matrix-only MATLAB function for neural network code
   % generation with MATLAB Coder tools.
   genFunction(net,'myNeuralNetworkFunctionSO2','MatrixOnly','yes');
   y = myNeuralNetworkFunctionSO2(x);
end
if (false)
   % Generate a Simulink diagram for simulation or deployment with.
   % Simulink Coder tools.
   gensim(net);
end
```

----

brSingPMFit.m

```
%  input data. and target data.
```

```
testData3=load('dataSingHu.csv')
testData4=load('dataBangHuMod.csv')
x = testData3;
t = testData4;

% Choose a Training Function
trainFcn = 'trainscg';  % Scaled conjugate gradient backpropagation.

% Create a Fitting Network
hiddenLayerSize = 5;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions

net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
global count3
count3  =0
for t1= 1:1:2300
e1(t1)=abs(e(t1))
if (e1(t1)>8)
    count3=count3+1
else
   count3=count3+0
```

```
end
end
if (count3>8)
disp('too many deviations')
else
disp('Normal situation')
end
performance = perform(net,t,y)
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

if (false)
   % network performs.
   genFunction(net,'myNeuralNetworkFunction');
   y = myNeuralNetworkFunctionC1(x);
end
if (false)
   % Generate a matrix-only MATLAB function for neural network code
   % generation with MATLAB Coder tools.
   genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
   y = myNeuralNetworkFunctionC1(x);
end
if (false)
   % Generate a Simulink diagram
   gensim(net);
end
```

*** *** *** ***

Extreme Learning Machine

```
function [TrainingTime, TestingTime, TrainingAccuracy, TestingAccuracy] =
elm_MultiOutputRegression(TrainingData_File, TestingData_File,
No_of_Output, NumberofHiddenNeurons, ActivationFunction)

%%%%%%%%%%% Load training dataset
train_data = csvread('trainDatage.csv')
%train_data=load(TrainingData_File);
No_of_Output = 2;
T=train_data(:,1:No_of_Output)';
P=train_data(:,No_of_Output+1:size(train_data,2))';
clear train_data;                          %   Release raw training data array

%%%%%%%%%%% Load testing dataset
test_data=csvread('testDatage.csv')
%test_data=load(TestingData_File);
TV.T=test_data(:,1:No_of_Output)';
TV.P=test_data(:,No_of_Output+1:size(test_data,2))';
clear test_data;                           %   Release raw testing data array

NumberofTrainingData=size(P,2);
NumberofTestingData=size(TV.P,2);
NumberofInputNeurons=size(P,1);

%%%%%%%%%%% Calculate weights & biases
start_time_train=cputime;

%%%%%%%%%%% Random generate input weights InputWeight (w_i) and
biases BiasofHiddenNeurons (b_i) of hidden neurons
%InputWeight= GSO()
InputWeight=rand(NumberofHiddenNeurons,NumberofInputNeurons)*2-1;
BiasofHiddenNeurons=rand(NumberofHiddenNeurons,1);
tempH=InputWeight*P;
clear P;                                   %   Release input of training data
ind=ones(1,NumberofTrainingData);
BiasMatrix=BiasofHiddenNeurons(:,ind);          %   Extend the bias matrix
BiasofHiddenNeurons to match the demention of H
tempH=tempH+BiasMatrix;

%%%%%%%%%%% Calculate hidden neuron output matrix H
switch lower(ActivationFunction)
    case {'sig','sigmoid'}
        %%%%%%%% Sigmoid
        H = 1 ./ (1 + exp(-tempH));
    case {'sin','sine'}
```

```
        %%%%%%%% Sine
        H = sin(tempH);
    case {'hardlim'}
        %%%%%%%% Hard Limit
        H = hardlim(tempH);
        %%%%%%%% More activation functions can be added here
end
clear tempH;                                    %   Release the temparary array for
calculation of hidden neuron output matrix H

%%%%%%%%%%% Calculate output weights OutputWeight (beta_i)
OutputWeight=pinv(H') * T';
end_time_train=cputime;
TrainingTime=end_time_train-start_time_train        %   Calculate CPU time
(seconds) spent for training ELM

%%%%%%%%%%% Calculate the training accuracy
Y=(H' * OutputWeight)'                          %   Y: the actual output of the
training data
TrainingAccuracy=sqrt(mse(T - Y))               %   Calculate training accuracy
(RMSE) for regression case
clear H;

%%%%%%%%%%% Calculate the output of testing input
start_time_test=cputime;
tempH_test=0.9.*TV.P;
clear TV.P;             %   Release input of testing data
ind=ones(1,NumberofTestingData);
BiasMatrix=BiasofHiddenNeurons(:,ind);              %   Extend the bias matrix
BiasofHiddenNeurons to match the demention of H
tempH_test=tempH_test + BiasMatrix;
switch lower(ActivationFunction)
    case {'sig','sigmoid'}
        %%%%%%%% Sigmoid
        H_test = 1 ./ (1 + exp(-tempH_test));
    case {'sin','sine'}
        %%%%%%%% Sine
        H_test = sin(tempH_test);
    case {'hardlim'}
        %%%%%%%% Hard Limit
        H_test = hardlim(tempH_test);
        %%%%%%%% More activation functions can be added here
end
TY=(H_test' * OutputWeight)'                    %   TY: the actual output of the
testing data
end_time_test=cputime;
```

```
TestingTime=end_time_test-start_time_test          %   Calculate CPU time (seconds) spent by ELM predicting the whole testing data

TestingAccuracy=sqrt(mse(TV.T - TY))            %   Calculate testing accuracy (RMSE) for regression case
```

Analog Sensor Data measurement and storing

```
import spidev # To communicate with SPI devices
from numpy import interp  # To scale values
from time import sleep  # To add delay
def main():
    # Start SPI connection
    spi = spidev.SpiDev() # Created an object
    spi.open(0,0)
# Read MCP3008 data
def analogInput(channel):
  spi.max_speed_hz = 1350000
  adc = spi.xfer2([1,(8+channel)<<4,0])
  data = ((adc[1]&3) << 8) + adc[2]
  return data

while True:
  output = analogInput(0) # Reading from CH0
  output = interp(output, [0, 1023], [100, 0])
  output = int(output)
  print("Moisture:", output)
  sleep(0.1)



    # use sys.argv if needed
    if len(sys.argv) < 2:
```

```
  print('Usage: python tstest.py PRIVATE_KEY')
  exit(0)
  print 'starting...'
baseURL = 'https://api.thingspeak.com/update?api_key=%s' % sys.argv[1]

  while True:
     try:
        w = output
        f = urllib2.urlopen(baseURL + "&field1=%s&field2=%s" % (w))
        print f.read()
        f.close()
        sleep(10)
     except:
        print 'exiting.'
        break
```

Appendix C

Data Sample

CENTRAL POLLUTION CONTROL BOARD

State Madhya Pradesh
City Singrauli
Parameter CO,SO2,PM10

Vindhyachal STPS, Singrauli - MPPCB

Prescribed Standards		NA	NA	NA
Exceeding Standards		NA	NA	NA
From Date	***To Date***	***CO***	***SO2***	***PM10***
01-01-2019 00:00	01-01-2019 04:00	0.55	13.29	418.81
01-01-2019 04:00	01-01-2019 08:00	0.51	12.31	342.38
01-01-2019 08:00	01-01-2019 12:00	0.32	10.14	382.81
01-01-2019 12:00	01-01-2019 16:00	0.16	23.72	273.69
01-01-2019 16:00	01-01-2019 20:00	0.51	57.59	321.88
01-01-2019 20:00	02-01-2019 00:00	0.74	21.46	629.79
02-01-2019 00:00	02-01-2019 04:00	0.57	13.13	451.5
02-01-2019 04:00	02-01-2019 08:00	0.56	13.64	358.21
02-01-2019 08:00	02-01-2019 12:00	0.25	10.91	408
02-01-2019 12:00	02-01-2019 16:00	0.13	15.76	278.25
02-01-2019 16:00	02-01-2019 20:00	0.43	35.14	527.06
02-01-2019 20:00	03-01-2019 00:00	0.48	15.96	429.3
03-01-2019 00:00	03-01-2019 04:00	0.52	12.36	440.38
03-01-2019 04:00	03-01-2019 08:00	0.48	11.87	357.69
03-01-2019 08:00	03-01-2019 12:00	0.32	13.25	444.12
03-01-2019 12:00	03-01-2019 16:00	0.11	6.76	234
03-01-2019 16:00	03-01-2019 20:00	0.25	11.01	231.88
03-01-2019 20:00	04-01-2019 00:00	0.49	13.3	449.31
04-01-2019 00:00	04-01-2019 04:00	0.43	12.79	638.81
04-01-2019 04:00	04-01-2019 08:00	0.43	12.83	322.94
04-01-2019 08:00	04-01-2019 12:00	0.29	9.41	394.69
04-01-2019 12:00	04-01-2019 16:00	0.08	8.39	191.94
04-01-2019 16:00	04-01-2019 20:00	0.48	17.59	342.94
04-01-2019 20:00	05-01-2019 00:00	0.56	14.96	445.21
05-01-2019 00:00	05-01-2019 04:00	0.42	12.36	363.12
05-01-2019 04:00	05-01-2019 08:00	0.39	11.89	235.25
05-01-2019 08:00	05-01-2019 12:00	0.3	19.28	290.12
05-01-2019 12:00	05-01-2019 16:00	0.14	32	228

CENTRAL POLLUTION CONTROL BOARD

CONTINUOUS AMBIENT AIR QUALITY

State	Odisha
City	Talcher
Station	Talcher Coalfields,Talcher - OSPCB
Parameter	Ozone,PM2.5
AvgPeriod	8 Hours
From	01-01-2019T00:00:00Z 00:00
To	31-12-2019T18:36:59Z 00:00

Talcher Coalfields,Talcher - OSPCB

Prescribed Standards		***0-180***	***0-60***
Exceeding Standards		***NA***	***NA***
Remarks			
From Date	***To Date***	***Ozone***	***PM2.5***
01-01-2019 00:00	01-01-2019 08:00	5.44	111.42
01-01-2019 08:00	01-01-2019 16:00	14.73	81.1
01-01-2019 16:00	02-01-2019 00:00	8.36	143.19
02-01-2019 00:00	02-01-2019 08:00	5.52	121.31
02-01-2019 08:00	02-01-2019 16:00	18.06	186.5
02-01-2019 16:00	03-01-2019 00:00	8.88	184.16
03-01-2019 00:00	03-01-2019 08:00	5.69	142.48
03-01-2019 08:00	03-01-2019 16:00	17.32	141.45
03-01-2019 16:00	04-01-2019 00:00	8.51	147.83
04-01-2019 00:00	04-01-2019 08:00	4.82	125.18
04-01-2019 08:00	04-01-2019 16:00	15.02	166.82
04-01-2019 16:00	05-01-2019 00:00	6.6	161.15
05-01-2019 00:00	05-01-2019 08:00	4.64	137.2
05-01-2019 08:00	05-01-2019 16:00	12.56	140.12
05-01-2019 16:00	06-01-2019 00:00	6.41	150.56
06-01-2019 00:00	06-01-2019 08:00	4.55	152.61
06-01-2019 08:00	06-01-2019 16:00	10.41	153.76
06-01-2019 16:00	07-01-2019 00:00	5.17	143.01
07-01-2019 00:00	07-01-2019 08:00	4.48	156.95
07-01-2019 08:00	07-01-2019 16:00	9.55	110.29
07-01-2019 16:00	08-01-2019 00:00	5.81	145.74
08-01-2019 00:00	08-01-2019 08:00	4.22	115.02
08-01-2019 08:00	08-01-2019 16:00	11.19	69.17

Appendix D

Response to Evaluation

Development of
Situational Awareness Platform
for the Safety in Mining

Response to Evaluation

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by:

B.RAMESH

Reg.No:

EE12P01

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY
KARNATAKA

SURATHKAL, INDIA-575025

Response to Thesis Reviewer Comments

Thesis Title: Development of Situational Awareness Platform for the Safety in Mining

Name of the Research Scholar: B Ramesh

Register Number: 123010EE12P01

Response to the Examiner's Queries

Q1. Software and Hardware co-design aspects used in the research

Sir,

The software and hardware co-design is considered in all three devices namely Arduino, arm 7, and raspberry pi. But most of the python software programs are with the raspberry pi 3-B as it is easier to upload data to the web using the Raspberry pi 3 B model which was the latest during the time of study and has a network connectivity. Calibrating and Converting the sensor data was done locally with Python programming. Hardware design needs to be manipulated for commercial use in future work.

Q2.Comment on the selection and justification of processor in terms of technical requirement and computing feature of the processors.

As the work was progressively done, Raspberry Pi 3B was the latest in that category of processors (in the year 2019). Recently, the Raspberry Pi 4 model has been released to the market.

Q3. What is the gateway used in the edge side of the proposed work?

Each sensor uses a standardized format for providing its parameter values (i.e., temperature, light, humidity, etc.). At the same time, supposing that a mechanism for the neighbor discovery is running; then, each sensor advertises its services. The gateway will be able to build its Neighbor Table, in which it will store data such as service name, timestamp of the last frame received from that neighbor, and connectivity statistics. That information is stored in a database and uploaded.

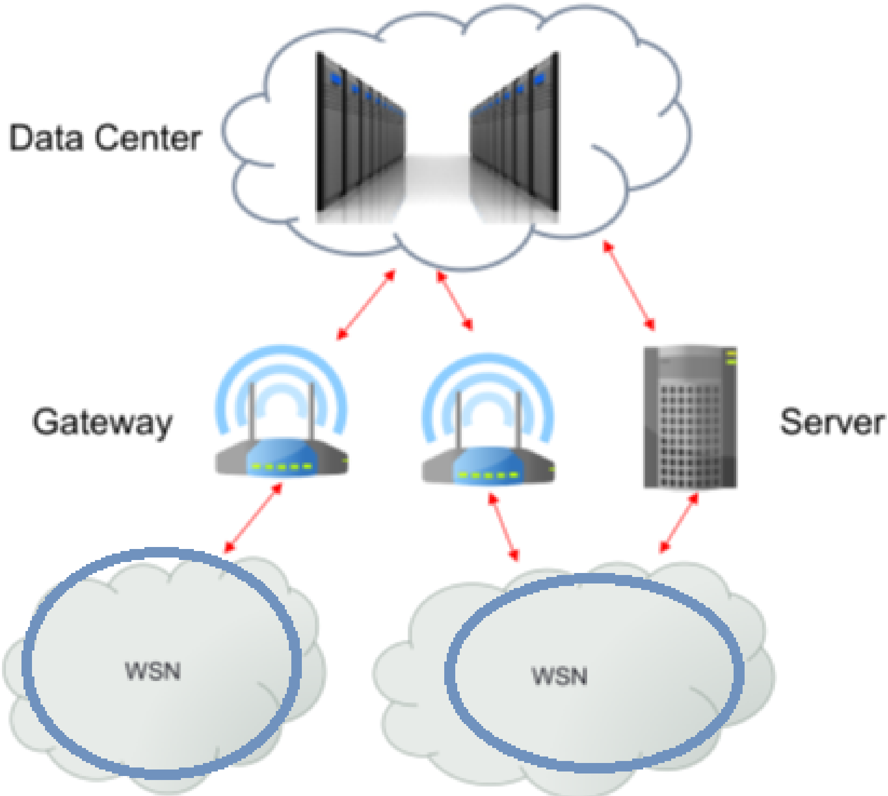


Figure 1: Gateway

The interactions of the gateway with sensors and/or other entities (Data Centers, local servers, etc.) are multiple and may occur depending on the particular use case. Along with the normal routing and forwarding functionality, the gateway can add further services by supporting more applications. The services have to be detected within the IoT scenarios, temporarily but in an efficient way.

The gateway information is appended to the report.

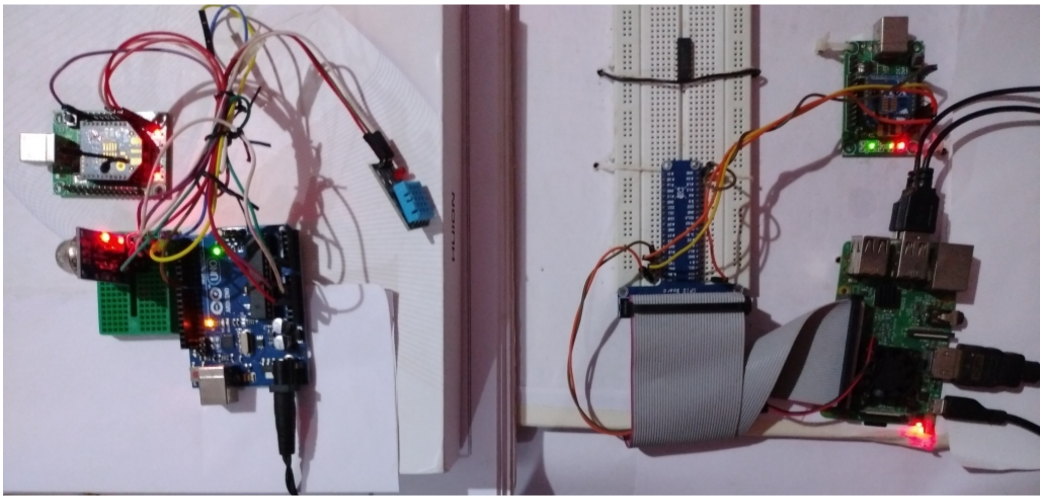


Figure 2: Example of Node and Gateway using Arduino and Raspberry Pi

Q4. How does the data will be communicating from the sensor node to the cloud? What levels of security features have been considered

ThingSpeak, an Internet of Things (IoT) application, uses the HTTP and MQTT protocol over the Internet or through a Local Area Network to store and retrieve data. It allows logging of sensor applications, tracing the location applications, and enables a network with its status updates. Originally launched by ioBridge in the year 2010, ThingSpeak was a service of IoT applications and now has a well-established relationship with Mathworks, Inc. It has support from the MathWorks of MATLAB software, letting users analyze and visualize data without the requirement of a MATLAB license from MathWorks. Every documentation of ThingSpeak is also included in the MathWorks' documentation site. All of the terms of service as well as the privacy policy in ThingSpeak.com are agreed in-between the user and Mathworks, Inc. ThingSpeak provides immediate visualizations of data given by the devices or equipment. Executing the MATLAB code in ThingSpeak, the online analysis could be performed and the data is processed as it comes in. ThingSpeak improves the development of beta-test of IoT systems, especially where analytics is required. One can build IoT systems without setting up servers or developing web software. For small to medium-sized IoT systems, ThingSpeak provides a good solution.

MathWorks follows the appropriate privacy laws, including but not limited to EU General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). Adhering to the fair information practice principles, they comply with principles like choice, security, data integrity and limitation of purpose, onward transfer accountability, access, enforcement, recourse, and liability. A sign-in with Mathworks is required for a user using ThingSpeak. MathWorks takes up the duty of storing any information a user provides for integrating ThingSpeak and MathWorks or any third-party services as credentials for authentication and code files. It also stores and chooses what data to send to ThingSpeak. A user can decide whether to make their data public or private. Public data is usually displayed with the MathWorks login account and links to the MathWorks account profile. Private data and apps are API keys protected that the user can reset at any time.

This information is appended to the report

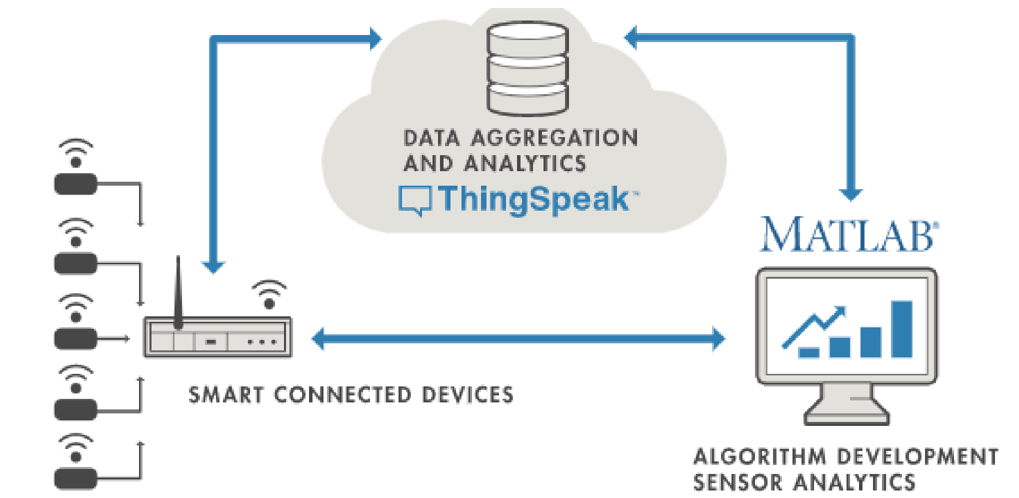


Figure 3: ThingSpeak

Users using devices, abide by basic security practices like changing default security passwords and blocking unnecessary remote access. Other steps should also include:

- Actively notifying users regarding devices that are running on outdated software or OS versions/
- Enforcing smart password management such as mandatory change of default password etc.
- Remote access to the device to be disabled unless necessary (for core functions.
- Including a strict access control policy for APIs.
- Protecting centers from attempts that compromise it.

The information regarding the security features of ThingSpeak are appended to the report.

Q5. What type of sensor network topology has been used in the network?

Star topology is used. star networks are connected to a centralized communication hub (sink) and the nodes cannot communicate directly with each other. The entire communication must be routed through the centralized hub. Each node is then a "client" while the central hub is the "server or sink".

Q6. What is the Latency in the network?

In a cloud edge, one will have a network separating servers from end-users. A device edge that places workloads directly on end-user devices can take the network out of the picture entirely (provided data both originates and is consumed at the edge, at least), which means latency ceases to be a consideration.

Testing network latency can be done by using ping or traceroute, although, comprehensive network monitoring and performance managers can test and check latency more accurately. Maintaining a reliable network is an important part of a smoothly operating project.

Q7. Is there any demarcation between edge and cloud computing in terms of decision making?

Bad network performance can become the bottleneck for the whole system. For example, particular IoT services, such as high-bandwidth sensors

(e.g., cameras), might have very strict latency requirements. A centralized Cloud would make these IoT services much more dependent on latency and delay issues without ensuring optimal performances.
On the other hand,moving part of the computation closer to the sensors and enabling ubiquitous computation, would bring several benefits. In most of the cases, all the operations described before have to be instantiated only temporarily, within a short period of time, and in an efficient way. Both a device edge and a cloud edge bring workloads closer to users to enhance performance. But they are different in certain key respects:

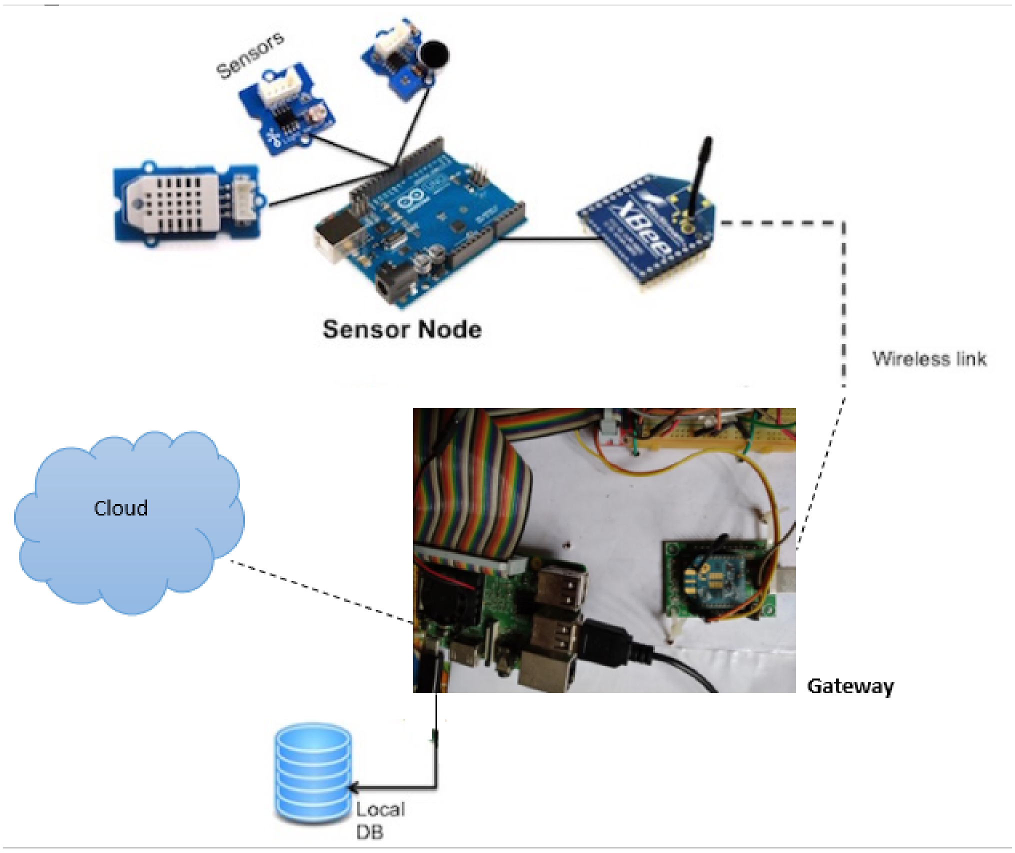


Figure 4: Raspberry Pi Gateway

A device edge (e.g., Raspberry Pi) is likely to have more limited compute, memory, and storage resources than a cloud edge(e.g, Thingspeak). One can only store and process data within the constraints of small-scale devices rather than having conventional servers.

Q8. Highlight the role of edge and cloud computing in the proposed work

Edge computing can apply to anything that involves placing service provisioning, data, and intelligence closer to users and devices.

Edge computing is any type of architecture in which workloads are hosted closer to the "edge" of the network which typically means closer to end-users than they would be in conventional architectures that centralize processing and data storage inside large data centers. By moving workloads closer to the users who need to access them, the edge can improve performance significantly, especially in contexts (like self-driving cars or automated manufacturing lines) where even just slight delays caused by network latency or bandwidth issues would be unacceptable.

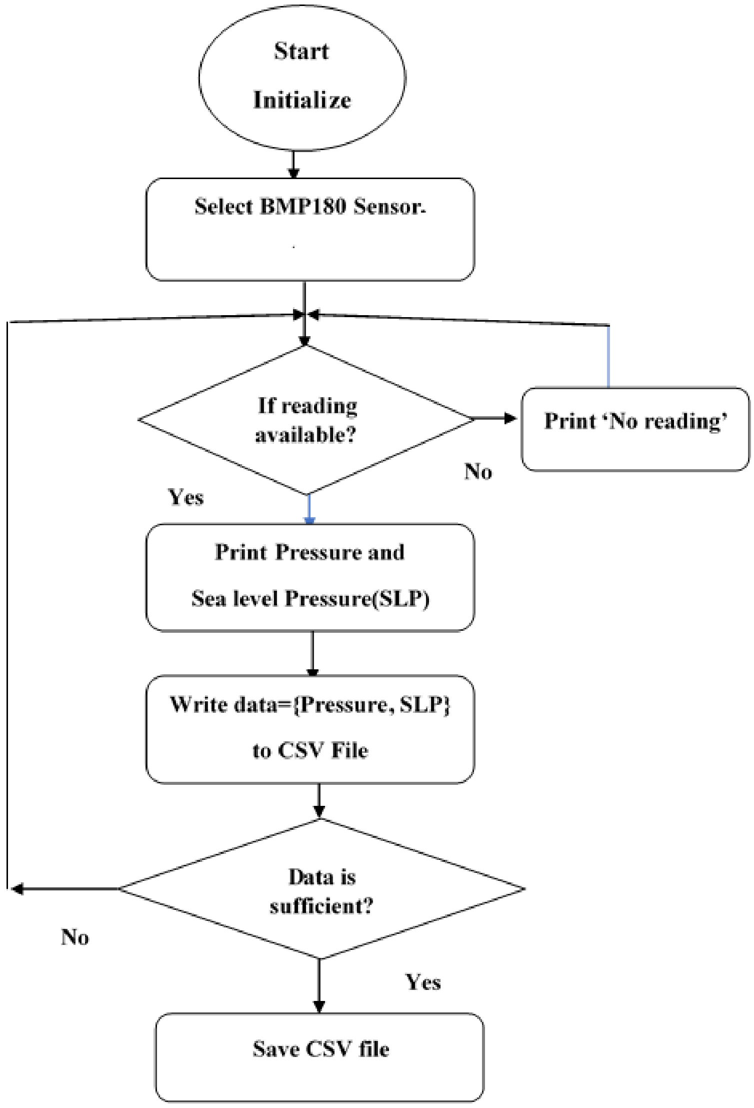


Figure 5: Flowchart

In other words, functions best handled by the computing split between the end device and local network resources will be done at the edge (in flowchart writing to CSV file), while big data applications that benefit from aggregating data from everywhere and running it through analytics and machine learning algorithms running economically in hyper-scale data centers will stay in the cloud Edge (saving to CSV file and uploading in flowchart). Basic Computation is done in the raspberry pi itself. (Figure.4)

Q9. Justify why Matlab based GUI has been used for the application development? Which may not be a suitable platform for the real time application.

The data collected on the web was analyzed using the Matlab-based GUI. It may not be suitable for real-time applications. But it can be easily transformed into real-time data collection using Labview or similar software-hardware combinations.

One can execute Matlab code directly in Labview provided one has the MathScript add-on. Or else one can always use ActiveX to talk to the Matlab execution engine. Mathscript supports a large set of functions within Mathscript. LabVIEW also has the Mathscript editor window, which looks similar to Matlab with an output window, variables, command window, and graphical sections.

Q10. Is the volume of data enough to predict the outcome reliable? Justify.

In my view, the volume of data is quite sufficient. The CPCB website provides enough data. If more data is required, timespan can be reduced to obtain more data.

Q11. Is the past data considered for the data analytics for a quick decision making and assess the safety conditions in the mine? If so explain how. If not why?

The past data is considered. The data is taken for the whole year of 2018 and 2019. The quick decision making as well as time series based long term decision making both can be analysed.

Q12. How does the verification of the prediction by the hardware and software modules has been done? What is the proof for the same?

The article in "Mongabay" newspaper dated 26 November, 2018 quotes-

- Communities living around coal mines and power plants in Singrauli are facing the brunt of extreme pollution which is impacting their health, access to education, employment and overall quality of life.
- The Central Pollution Control Board and the National Green Tribunal

have expressed concerns about the unabated push for coal in the region but there is no visible improvement in the lives of the locals.

Q13. Why is the neural network considered for this application? Justify.

Neural network linear and curve fitting regression was giving a proper decision making analysis by showing the trend of variation with graphical presentation.

Q14. Sensors have some levels of accuracy; has the candidate calibrated the sensors or balanced the errors in the data analytic to arrive at the exact value.

Some of the sensors are calibrated with comparison with standard equipment. For instance, temperature, pressure measurements are calibrated.

Q15. How does the false data in the data analytics filtered?

The false data is visible which is completely out of normal variation. These are eliminated by the software.

Q16. Why is the Xbee communication used in the data collection process? How are the line of sight issue and pocket drop issues addressed to achieve reliable data communication?

In the area of wireless sensor networks, a design standard is developing to incorporate Xbee series 2 as a wireless bridge between Arduino or Raspberry Pi sensor and data aggregate nodes. In this thesis, I constructed an Xbee series 2 ZigBee wireless star topology network, with an Arduino as a ZigBee end device, and a Raspberry Pi as the ZigBee network coordinator.

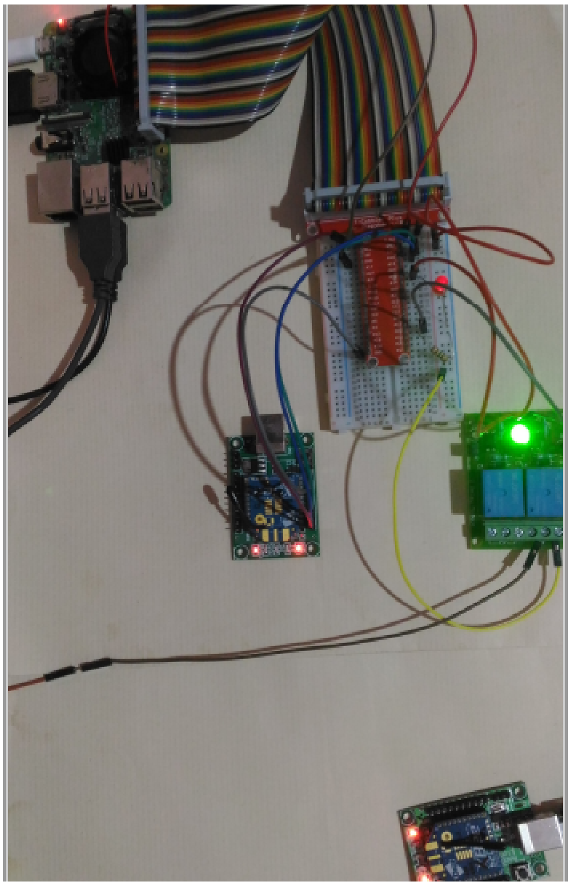


Figure 6: XBees Communicating

Xbee uses API mode 2 for package formation and transmission. Xbee communication gave better control of raspberry pi. The line of sight issue could be tackled by increasing the number of nodes, and increasing the range of transmitters like the LoRa (Long range) node in future works. The Lora node device is being acquired. LoRa uses spread spectrum technology which eliminates the line of sight issues.

This information is appended to the report

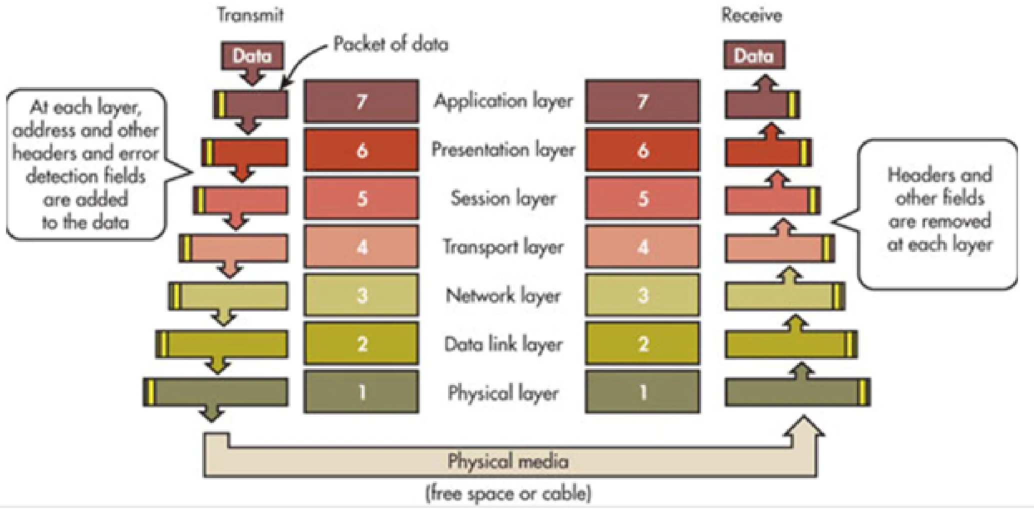


Figure 7: Network Layers

Q17. Why the candidate has used Aurdino, Arm-7, and Raspberry-pi processor for their particular application as there are better SoC platform in the market for this kind of applications? None of these processors used by the scholar for this research work have gateway features to put the data into the cloud.

Sir,During the year 2019, Raspberry Pi 3B was latest and hence it was used. For the previous work, Arduino and Arm-7 was used as Arduino can be used together with Raspberry Pi easily like a node. Recently Raspberry Pi 4 is launched which can be used in future work

Other Queries

Q. Grammatical errors and formatting errors

Sir, The whole document is grammar-checked. Some figures are resized to the width of the text. Singrauli photo is replaced with a more appropriate photo.

Q. Chapter 1 to be modified

Chapter 1 which is the introduction chapter is rearranged. But objectives are stated in chapter 2 after the literature review. There was no objection from the other evaluator. If necessary it can be moved to the introduction chapter.

Q. The literature review should include national and international developments.

Sir, the literature review chapter is modified.

Q. Product brochures may not be necessary

The data sheets are replaced by links.

Q. The title will not gel with work. Work was not near mine.

Sir, as the Singrauli mine is an open-pit mine, and already there was the availability of data of the area, it was used to find the effect near the mine. The title could be changed if allowed by the regulations. **Q. Sensor data is not from the mining area**

As the open atmospheric pollution can be measured, it can be applied near the mine also. My electronic devices cannot be taken to a mine due to safety issues.

Q. What is the base to use only five parameters?

Sir, The measured five parameters are the major contributors to the pollution near mining.according to Mishra and Das (2020), particulate matter is the main pollutant near Talcher. NO_2 is an additional pollutant that is generated due to fire. This could be included in future work.

Q. The conclusion and future scope needs modification

Sir, the future scope is modified in the report. **One more scope is added in the report, namely:** "Gateway hardware like LoRa Gateway could be used to upload many sensors' data to the cloud over long distance. The security issue can be researched upon".

Q. How the present research can enhance safety at the mine site.

Sir, The present work is an initiative to provide some IoT-based research near the mining site. The data collection and analysis will provide an additional safety level for the mining activity.

Q. How the present work is different from previous research

Sir, If this work is implemented, it will provide real-time observation of the mining area in a cost-effective way using web resources. The work is also using some of the IoT concepts which were not done before.

Appendix E

Resume

CURRICULUM VITAE

RAMESH BANTWAL

PERMANENT ADDRESS:
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Padil, Bannur P.O, PUTTUR
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SUMMARY OF QUALIFICATIONS:	M. Engg (Control &Instrumentation), B. Engineering (Electrical), PhD (pursuing)
WORK EXPERIENCE:	***July 2017- To date: Asst Professor, EEE, CIT, Gubbi, Tumkur*** ***Jan 2015- Apr 2017 : Sr Associate Professor,E&CE, AIET, Moodbidri*** Sr Associate Professor: Successfully organised one workshop for faculty and one for students. ***Jan 2013- To Date:*** *Research Scholar(FT/PT), NITK, Surathkal* ***Jan 2011- Dec 2012:*** *K.V.G College of Engineering* *Assistant Professor/ Associate Professor: Electrical* -Theoretical and practical training. -Departmental placement coordination. ***Feb 1998 – Oct 2010****: PALAPYE TECHNICAL COLLEGE, PALAPYE, BOTSWANA:-* **SENIOR LECTURER/HOS/HoD: Instrumentation** -Theoretical and Practical training of students. -Guiding the student's projects. -Procurement of sectional equipment and materials. -Worked as Safety Coordinator. ***Apr 1994 – Jan 1998****:NMAM INSTITUTE OF TECHNOLOGY, NITTE, INDIA:-* **SENIOR LECTURER/ASSISTANT PROFESSOR**: Electronics Department -Practical training of undergraduate students in Power Electronics, Analog Electronic circuits, Digital Electronic circuits and microprocessors.

	-Lecturing on: Industrial process control, Digital Signal Processing, Microprocessors, Electronic Measurements. ***Sep 1989 – Sep 1992****:NMAM INSTITUTE OF TECHNOLOGY, NITTE, INDIA:-* **LECTURER** - Electrical/ Electronics Department -Lecturing Electrical subjects: Electrical machines, Electrical Circuits, Electrical Measurements, Power system, Switch gear and protection. -Practical training of Electrical and Electronics degree students
EDUCATION:	***Research Subjects:*** *Power System Modelling and Analysis, Computer-Aided Protection of Power Systems.* ***M. Engineering:*** Instrumentation and Control, 1994, MLN Regional Engg. College, Allahabad University, India. (75.2%) **Subjects:** Linear System Theory Instrumentation Digital Signal Processing Optimal Control Biomedical Instrumentation Thesis. Signals and Systems Optimization Techniques Industrial Process & Control Network Synthesis Instrumentation & Control Lab ***B. Engineering****:* Electrical Power, 1988, PDA Engg College, Gulbarga University, India. (72.5%) **Final Year Subjects:** Power System Analysis & Stability Switchgear & Protection Design of Electrical Machines Engineering Economics& Industrial Managt. Power System Lab Project work. Computer Tech Power Electronics Electrical Drives, Instrumentation Electronics Lab ***MBA:*** 2005, MANCOSA, RSA (Dist Edu) -National Certificate in datametrics (University of South Africa)
ACCREDITATIONS:	Qualifications are accredited by New Zealand Qualifications Authorities.
PROFESSIONAL MEMBERSHIP:	- Member of Institution of Engineers India (IEI) -Life member of ISTE
ACHIEVEMENTS:	-Setting up of Instrumentation lab in PTC, Botswana -Conduction of staff and student workshops and technical talks in AIET

M.TECH THESIS	-Design of Digital Filters and digital algorithms for distance protection (M.E)
PAPERS PUBLISHED	**<u>Journals:</u>** 1. **Ramesh B and Vittal K P**,(**2017).** "An ontology aided GSO optimized extreme learning for situation recognition in coal mining environment", Journal of Advanced research in dynamical and control systems, ISSN 1943-023X, Vol.9,sp-14, pp.1569-1590. H-Index 21. 2. **Ramesh B and Vittal K P**(**2018),** "wireless sensor networks for situation awareness in coal mining environment", Journal of computational and theoretical Nanoscience, ISSN 1946-1955 (Print), 1946-1963 (Electronic),Vol.15,sp-14, pp.2242-2244, H-Index 52. 3. **Ramesh B and Vittal K P (2019)**,"Situation awareness of deep mining environment using raspberry pi", Journal of computational and theoretical Nanoscience, ISSN 1946-1955 (Print), 1946-1963 (Electronic), Scopus index Vol 6, pp.2604-2608. H-Index 52. **<u>Conferences:</u>** 4. **Ramesh B, and Vittal, K.P(2015),** "Upgrading Substation Relays to Digital Reclosers and their Coordination with Sectionalizers". *Proceedings of 4th IRF International Conference 85-89.* 5. **Ramesh B, and Vittal, K.P(2018),** "wireless sensor networks for situation awareness in coal mining environment", ICRTET, June 2018, Vemana Institute of Technology, Bangalore. 6. **Ramesh B and Vittal K P, (2020)."**Wireless monitoring and control of deep mining environment using ThingSpeak and Xbee", ICIDCA, Springer Conference. IEEE XPLORE COMPLIANT ISBN - 978-0-7381-4627-0, IEEE DVD ISBN - 978-0-7381-4626-3

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