IoT Station for Health Monitoring in Underground Mining Using Compressive Sensing Architecture

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***Abstract*— This study addresses health and safety risks in the underground mining by developing an Internet of Things (IoT) Station using compressive sensing architecture to monitor vital parameters such as heart rate, body temperature, carbon monoxide (CO) levels, and environmental temperature in real-time manner. Data transmission is facilitated through a LoRa wireless network utilizing a star multihop topology, which allows sensor modules to first send data to a central LoRa transceiver before relaying it to a main base station. The communication module extends coverage and enhances data reliability, making it suitable for challenging underground environments. Simulation and testing demonstrated effective communication up to 1.6 km in open areas and 1 km in closed areas, with stable data transmission. This multihop approach reduces accident risks and enhances safety and productivity by ensuring comprehensive monitoring across extended areas. The Compressive Sensing architecture improves bandwidth and energy efficiency by reducing the data volume by up to 50% without losing important information. In addition, the system employs thresholding to classify conditions into 'safe,' 'alert,' and 'danger' categories based on specific ranges for humidity, CO levels, temperature, and heart rate.**

Keywords — Internet of things, compressive sensing, real-time monitoring, LoRa network, mining health.

I. INTRODUCTION

The mining industry is one of the sectors with high potential risks related to the health and safety of workers. Therefore, innovation in technological development is needed to help identify and mitigate these risks. One potential solution is the use of IoT-based safety vests to monitor the health and safety of mining workers. These vests can anticipate accidents and injuries, monitor workers' health, ensure traffic safety, and improve workers' quality of life.

Factors such as toxic gas concentrations, extreme temperatures, and high humidity can threaten workers' safety if not effectively monitored. Monitoring systems are an urgent need to mitigate these risks. The Internet of Things (IoT) offers an innovative approach through the collection, processing, and analysis of real-time mine environmental data, enabling faster and more accurate data-driven decision-making [1].

The development of IoT-based safety vests involves research and development costs for hardware and software. The potential economic benefits include increased productivity, reduced costs from workplace accidents, and savings through improved worker health monitoring. These vests also provide extra protection against physical risks in the mining environment and help prevent serious injuries or fatal accidents. The use of environmentally friendly materials and sustainable production processes is also important for the product's sustainability.

In this study, we developed an IoT station that integrates Compressive Sensing (CS) architecture to monitor critical environmental parameters. The compressed data is transmitted via a LoRa (long range)-based wireless network, which has advantages in power efficiency and wide coverage [2]. This system is designed to improve monitoring efficiency while overcoming the limitations of IoT technology in challenging mining environments. Through the implementation of this solution, we hope to make a significant contribution to improving occupational safety in underground mines and support further development towards artificial intelligence-based systems for automatic risk detection and mitigation.

Several studies have been conducted on IoT-based mines monitoring. In [3], the authors explore the implementation of a monitoring system aimed at preventing thermal events in mining and landfill waste disposal sites. Data-driven insights enabled operators to take preventive measures, reducing the likelihood of thermal events.

However, conventional safety systems in mines may be less responsive to real-time changes in situations. A more adaptive and proactive solution is needed to address the continuously evolving safety challenges. Mine workers may also be exposed to environmental conditions that can affect their health. Safety vests have become an integral part of worker protection across various industries. Designing safety vests equipped with IoT technology can be an innovative step to enhance safety and worker monitoring in the mining environment.

II. STATE-OF-THE-ART

A. Networking

IoT is a concept that enables physical devices to connect with each other and the internet, collecting and sharing data in real-time. These devices, such as sensors or actuators, can interact with their surroundings and central systems, facilitating automatic monitoring and control. IoT applications in underground mining include monitoring hazardous gases such as methane and carbon monoxide; measurement of temperature, humidity, and structural stability; and tracking of worker location.

LoRa is a low-power wireless communication protocol designed for long-distance communication, making it ideal for IoT applications. LoRa operates in unlicensed frequency spectrums and allows data transmission over several kilometers with minimal power consumption [4]. It is used in the LoRaWAN communication standard, which connects IoT devices to gateways and subsequently to the internet. It can be deployed as star or partial mesh topology. This central point acts as a communication controller, ensuring that a failure in one device does not affect the entire network.

On the other hand, ESP-NOW is a wireless communication protocol developed by Espressif, allowing ESP32 or ESP8266 devices to communicate without a Wi-Fi network stack. This protocol is efficient in power consumption, offers low latency, and provides a longer range compared to Wi-Fi. It can be implemented in a star topology, allowing edge devices to send data directly to a central node. To extend the range, ESP-NOW can be combined with LoRa, forming a partial mesh or tree topology that increases the communication range up to 5 km in rural areas and 2 km in urban areas. This evaluation of LoRa technology as an alternative communication protocol highlights its effectiveness in enhancing network range and reliability in low-power, long-distance applications.

Spreading Factor (SF) in LoRa is a parameter that determines the number of bits sent per symbol [7]. SF values affect the range and data speed. Lower SF values (e.g., SF7) provide higher data speeds but shorter range, while higher SF values (e.g., SF12) offer a longer range but lower data speed. The choice of SF must be tailored to the specific needs of the application, balancing the need for longer range versus higher data speed.

The combination of these technologies enables the development of efficient and reliable IoT systems for real-time monitoring of workers and environmental conditions in the mining industry.

B. Compressive Sensing

CS is a signal processing technique that enables simultaneous sampling and compression of data. The core principle of CS is that sparse signals in certain domains, such as frequency, can be represented with far fewer samples than required by conventional sampling theories like Nyquist-Shannon [8]. This reduces the amount of data to be stored or transmitted without losing critical information. In IoT applications, particularly in resource-constrained environments like underground mines, CS helps save bandwidth and power, as well as real-time analysis. By integrating IoT technology, CS can be an effective solution for health and safety monitoring in underground mines, where extreme working environments require reliable and resource-efficient monitoring systems.

However, the implementation of IoT in underground mines faces several challenges, including limited communication bandwidth, high power consumption of devices, and difficulties in managing the big data generated by sensors [5] [6]. This is where compressive sensing becomes relevant, as it allows for resource savings while maintaining the data accuracy required to monitor environmental conditions and worker health. CS in our scheme consists of three main stages:

1. Compressed sampling: Data is captured in a transform domain with a random measurement matrix. The volume of data collected is much smaller compared to traditional sampling methods.
2. Data Transmission: Compressed data requires less bandwidth, thus saving power and transmitting faster.
3. Signal Reconstruction: Data received at the server is processed using algorithms such as basis pursuit or orthogonal matching pursuit (OMP). The original signal is reconstructed for further analysis.

In the context of CS, Fast Fourier Transform (FFT) transforms signals from the time domain to the frequency domain, where they can be more sparsely represented [5]. This frequency representation is then compressed using CS. FFT enables faster and more efficient signal processing, making it essential for analyzing large and complex datasets. In underground mining health monitoring systems, FFT allows for the quick identification of significant changes, such as hazardous gas levels or sudden shifts in workers' heart rates.

$$x(f) = \mathrm{FFT}(x(t)) \qquad (1)$$

$x(f)$: signal in frequency domain
$x(t)$: signal in the time domain

Gaussian and Bernoulli processes also play a role within CS frameworks, particularly in modeling and predicting sensor behavior. A Gaussian distribution is often used for its properties of simplicity and flexibility in modeling real-world data, making it a valuable tool for analyzing noise characteristics and variability in sensor signals. In this study, Gaussian noise models can be applied to simulate realistic conditions where sensor readings might be corrupted by environmental factors. By accounting for Gaussian noise, the accuracy and robustness of CS in processing health monitoring data are enhanced, making it possible to detect anomalies with greater reliability. A random Gaussian matrix has entries sampled from a Gaussian distribution:

$$\Phi_{ij} \sim \mathcal{N}\left(0, \frac{1}{M}\right)$$

Where $\mathcal{N}\left(0, \frac{1}{M}\right)$ is a normal distribution with mean 0 and variance 1/M.

On the other hand, a random Bernoulli matrix is a type of measurement matrix widely used in CS, where each element is independently sampled from a Bernoulli distribution. Typically, entries are either $+1/\sqrt{M}$ or $+1/\sqrt{M}$ with equal probability (0.5). Random Bernoulli matrices are particularly suitable for resource-constrained environments due to their low storage requirements and fast matrix-vector multiplications.

OMP is a commonly used signal reconstruction algorithm. It reconstructs the original signal from compressed samples by selecting the atoms from a basis that best matches the observed signal [6]. OMP is known for its simplicity and strong performance in reconstructing sparse signals. In this study, OMP is used to reconstruct data from compressed sensor signals, ensuring that the integrity of health monitoring data is maintained. Data reconstruction in OMP involves matching between the observed signal and a sparse representation in the form:

$$\boldsymbol{y} = \boldsymbol{\Phi x} + \boldsymbol{e} \qquad (2)$$

where y is the observation vector (measured signal) with dimension of m, Φ is the basis matrix or dictionary, x is the sparse coefficient vector (dimension of n), and e is the noise vector or measurement error.

We can find the least squares solution using the selected atoms:

$$x_{S_{k+1}} = \arg\min_{z} \left\| y - \mathbf{\Phi}_{S_{k+1}} \boldsymbol{z} \right\|_2 \quad (3)$$

Then calculate the new residual:

$$r_{k+1} = y - \mathbf{\Phi}_{S_{k+1}} \mathbf{x}_{S_{k+1}} \quad (4)$$

r_{k+1} is the residual at iteration k + 1, Φ_S is matrix constructed on the selected columns, and x_S is coefficients of the signal representation.

C. *Thresholding*

We applied thresholding as a processing technique used to categorize data into specific groups [7]. In this monitoring system, the thresholding function is employed to classify sensor data into safe, alert, or danger categories. This technique enables the system to issue warnings or trigger automated actions in response to detected environmental conditions, enhancing the responsiveness to potential hazards in mining environments. By employing adaptive thresholding, the system can also adjust its sensitivity to varying conditions, providing more accurate and timely alerts based on real-time data fluctuations. This approach further reduces the likelihood of accidents by allowing for proactive safety measures.

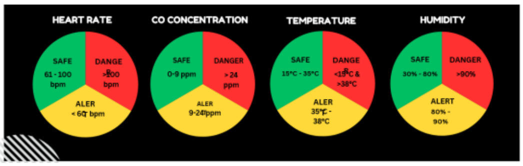

Figure 1. Sensor Value Thresholding

III. METHOD

Given the requirements which involve preventing and minimizing risks in underground mining, such as harmful temperatures and humidity levels, the risk of exposure to toxic gases like carbon monoxide, and the need for heart rate monitoring, the device is designed to monitor these underground conditions effectively. Utilizing methods like FFT and Gaussian or Bernoulli projection, the data is compressed and then reconstructed using OMP. This approach ensures that critical information regarding environmental conditions and health parameters is accurately captured and relayed.

A. *Networking*

The following figure depicts an IoT system with a star topology where some ESP32 connects to sensors sending data to LoRa transceiver that acts as a gateway, which then sends the data to the database for further storage and analysis. The system workflow is as follows: (1) Data is collected by sensors and compressed at the IoT node; (2) The compressed data is transmitted via a gateway to a server or cloud; (3) The server performs signal reconstruction and analysis to detect anomalies or hazardous conditions; and (4) Critical information is sent back to the mine operator for decision making.

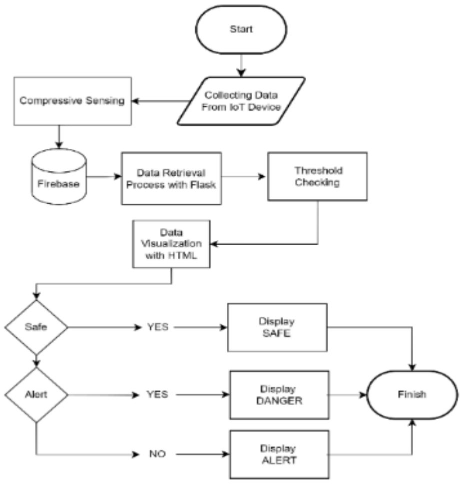

Figure 2. Overall System Flowchart

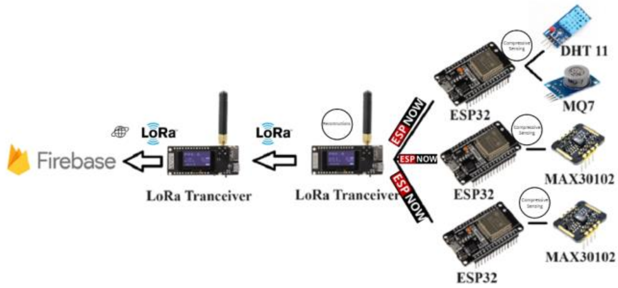

Figure 3. Network Topology

The image depicts the architecture of an IoT-based health monitoring system for underground mining, utilizing various components such as sensors, ESP32, LoRa transceiver, and data storage. ESP32 collects data from the sensors and sends it to the nearest LoRa transceiver. The data from the first LoRa transceiver is then transmitted to a second LoRa node, which may function as a gateway or base station. Firebase stores this data, making it accessible for real-time monitoring, analysis, and further actions if necessary.

In this research, the process begins with data collection from various sensors, including the MQ7, DHT11, and MAX30102, which respectively detect carbon monoxide concentration, measure temperature and humidity, and monitor heart rate. The collected data is then transmitted via a LoRa network to the database.

B. *Compressive Sensing*

Compressive Sensing enables efficient data collection by reducing the number of required samples. This can overcome bandwidth limitations and optimize resource utilization. Compression algorithm development involves 2 main stages. Firstly, the selection of sparsifying matrix: FFT is used in this study. Secondly, data projection in IoT nodes: simple random matrices such as Gaussian or Bernoulli matrices are used to ensure compression can be performed with minimal resources. The compression level is adjusted based on the sensitivity of the data (e.g., heart rate data has higher priority than humidity).

The data acquisition method on the transmitter side using FFT allows IoT devices equipped with sensors such as DHT (for measuring temperature and humidity), MAX30102 (for monitoring health parameters like heart rate and blood oxygen levels), and MQ7 (for detecting carbon monoxide concentration) to continuously collect data. This raw data is then transformed using FFT to identify the dominant frequency coefficients. The FFT makes the data easier to analyze in terms of its coefficients, which can be very useful for detecting patterns and features that may not be visible in the time domain. After the transformation, the data is transmitted to the data processing center through the IoT network.

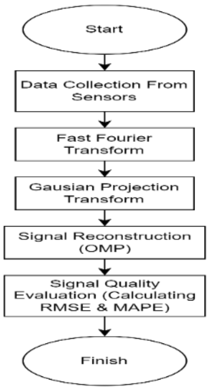

Figure 4. Compressive Sensing Flowchart

The data reconstruction method used on the receiver side is OMP. It is an efficient approach to integrating and managing data from various sensors. The data is then transmitted to the processing center through the IoT network. The OMP algorithm helps optimally identify patterns and anomalies in the data, enabling more accurate and real-time analysis. This analysis is used to make better and more responsive decisions in response to changes in environmental and health conditions, as well as to improve the overall efficiency and reliability of the IoT system.

C. Application

This research uses a prototype-based development method to design and build an application for monitoring and predicting hazardous conditions in mining environments. The research process was conducted in several stages, including system design, technology implementation, and application testing.

The system design stage involves identifying the requirements for monitoring the mining environment, including determining the types of sensors to be used, selecting the data processing devices, and choosing the appropriate communication technology such as ESP32 and LoRa Transceiver. Additionally, this stage includes designing the system architecture that integrates the sensors, Firebase as the data storage solution, and the Flask framework as the web interface.

In the implementation stage, sensors are connected to the ESP32 and LoRa Transceiver to facilitate data transmission. The real-time database is then configured to store and synchronize the sensor data in real-time. Furthermore, a user interface is developed using HTML to display the sensor data in an interactive dashboard, with Flask serving as the backend framework.

IV. Results and Discussion

A. Network Testing

This research conducted two tests with 1.6 km for LOS (Line of Sight). The first test was carried out from an elevated area to a lower elevation, simulating real-world conditions where LOS is maintained across varying terrains. The lower elevation helped evaluate the transmission performance in conditions where the receiver is at a lower altitude compared to the transmitter.

The second test, NLOS (Non-Line of Sight), was conducted in a forested area known for its dense vegetation and rugged terrain. Specifically, the transmitter was placed inside subterranean structures, simulating underground mining environments, while the receiver was located outside the cave at 1 km. This setup was chosen to replicate the challenging conditions of mining sites, where signal propagation is affected by physical obstructions and materials with high attenuation properties, such as rock and soil.

For the LOS test, the experiment was conducted over 1.6 km, maintaining a clear LOS to assess the maximum transmission range and signal quality. The selection of a location with varying elevation and open spaces provided realistic insights into signal behavior in both urban and natural environments.

Mine health and environmental monitoring involves measuring various parameters, i.e. hazardous gases like the concentration of carbon monoxide (CO) to prevent fire or explosion, environmental conditions such as temperature and humidity to detect significant environmental changes, and worker health such as heart rate, blood oxygen, and physical activity to ensure worker safety and health.

Table 1 LoRa NLOS Test Result

Spreading Factor	Distance (Km)	RSSI (dBm)			SNR (dB)	Throughput (bps)	Latency (s)	BER (%)
		Max	Min	Average				
SF7	1	-45	-118	-80.26	6.73	36.83	18.07	0.0816
SF12	1	-20	-121	-89.32	1.22	5.58	34.5	0.4559

The Spreading Factor (SF) in a LoRa network significantly impacts various aspects of communication performance. When the SF is increased from SF7 to SF12, several notable changes occur. First, throughput drastically decreases from 164.84 bps at SF7 to 42.26 bps at SF12. Second, latency increases from 9.41 seconds at SF7 to 12.92 seconds at SF12. However, the Bit Error Rate (BER) decreases from 0.9% at SF7 to 0.1% at SF12, indicating that the bit error rate is reduced. Additionally, the Signal-to-Noise Ratio (SNR) decreases from 6.28 dB to 4.01 dB. Overall, increasing SF improves communication reliability in poor signal conditions but at the expense of data transmission efficiency and speed.

For the NLOS test, we conducted the experiment in the caves located in Bandung, Indonesia. In this test, we performed two measurements, one with SF 7 and the other with SF 12. The average measurement results are as follows.

Table 2 LoRa LOS Test Result 1

Spreading Factor	Distance (Km)	RSSI (dBm)			SNR (dB)	Throughput (bps)	Latency (s)	BER (%)
		Max	Min	Average				
SF7	1.6	-46	-114	-89,6	6.28	164.84	9.41	0.9
SF12	1.6	-37	-126	-90,5	4.01	42.26	12.92	0.1

The change from SF7 to SF12 has several significant impacts. Increasing the SF from 7 to 12 results in lower throughput, dropping from 36.83 bps to 5.58 bps. Additionally, latency nearly doubles, increasing from 18.07 seconds at SF7 to 34.5 seconds at SF12. The SNR drops from 6.73 dB to 1.22 dB, indicating more interference in the signal. The BER also increases from 0.08% at SF7 to 0.46% at SF12. Overall, increasing SF enhances the range and reliability of communication in poor signal conditions but reduces data transmission efficiency and speed.

B. Compressive Sensing Testing

Here are the results of the compressive sensing test results.

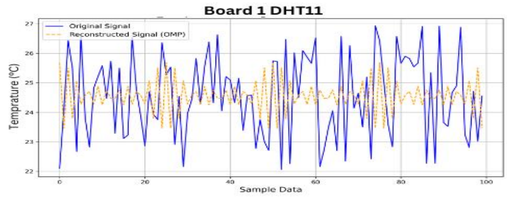

Figure 5 Test Results of Compressive Sensing Temperature

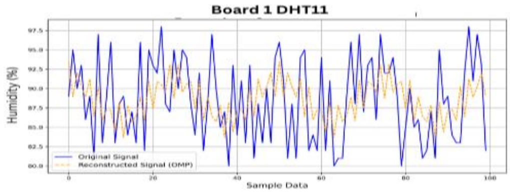

Figure 6 Test Results of Compressive Sensing Humidity

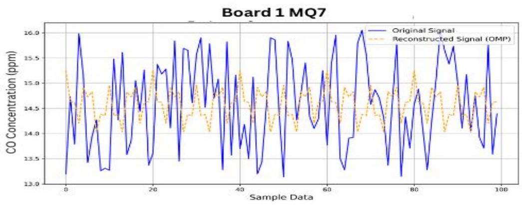

Figure 7 Test Results of Compressive Sensing CO Concentration

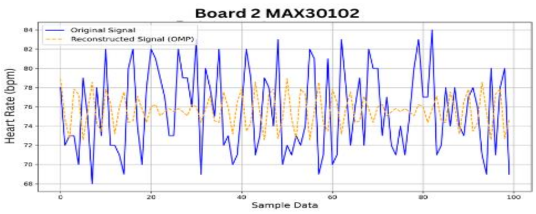

Figure 8 Test Results of Compressive Sensing Board2 Heart rate

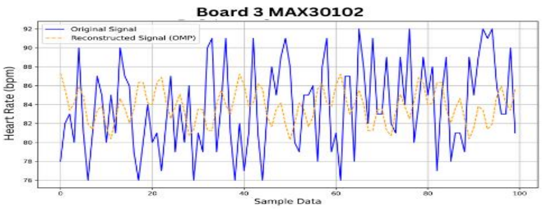

Figure 9 Test Results of Compressive Sensing Board3 Heart rate

Implementing Compressive Sensing techniques using the OMP algorithm on data collected from DHT11, MQ7, and MAX30102 sensors. The processes of measurement, compression, and signal reconstruction are carried out systematically and efficiently. The reconstruction results show that the OMP algorithm can reconstruct the original signal with adequate accuracy, allowing for savings in data storage and transmission, as well as improving the overall performance of the sensor system. The following RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) values are presented.

Table 3 RMSE and MAPE Value for Various Measurement Matrices

Sensor	Random Gaussian		Random Bernoulli	
	RMSE	MAPE (%)	RMSE	MAPE (%)
Humidity	4.84	4.7	4.05	3.8
MQ7	1.05	6.13	2.1	5.2
Temperature	1.63	5.6	3.7	4.8
Heartrate Board 2	5.12	5.86	4.2	5.17
Heartrate Board 3	5.43	5.5	3.6	4.8

The table summarizes the performance of various sensors in terms of RMSE and MAPE. The MQ7 sensor, used for measuring CO levels, shows the lowest RMSE (1.05) but has the highest MAPE (6.13%), indicating that while the absolute error is low, the percentage error relative to the measured values is higher. The temperature sensor displays moderate RMSE (1.63) and MAPE (5.6%), suggesting balanced accuracy. The humidity sensor, with an RMSE of 4.84 and a MAPE of 4.7%, indicates a relatively higher absolute error but maintains a lower percentage error. The heart rate sensors (Board 2 and Board 3) exhibit similar performance, with RMSE values of 5.12 and 5.43, and MAPE values of 5.86% and 5.5%, respectively. Overall, the sensors demonstrate varying levels of accuracy, with the MQ7 sensor showing the best absolute error but the most significant percentage error.

We performed calculations to measure data compression efficiency during the acquisition process. First, we set a measurement rate of 5%. This measurement rate is calculated using a formula that measures the percentage of output coefficients from the acquisition process compared to the total number of input samples. The result indicates that only 5% of the input samples are required to represent the data in output form, demonstrating high efficiency in the sampling process.

$$Measurement\ rate = \frac{C}{S}\ x\ 100\ \%\ (3)$$

$C =$ samples from the acquisition process output
$S =$ samples from the acquisition process input

Additionally, we conducted signal reconstruction analysis using the OMP method. From this reconstruction process, we achieved a highly significant compression ratio of 0.05. This compression ratio means that the reconstructed signal only requires 5% of the components present in the original signal to represent the same information. This indicates that the original signal contains a substantial amount of redundancy, which can be eliminated without losing critical information.

$$\text{Compression Ratio} = \frac{\text{Output Size}}{\text{Input Size}} \quad (4)$$

IoT systems based on CS show significant reduction in data volume. Comparison between traditional sampling methods and CS shows that compressed data has an average size of 60–70% smaller. Also, communication bandwidth usage is reduced by up to 50%, even in poor transmission conditions such as mines with signal obstructions or NLOS.

C. Application Testing

We develop a monitoring and prediction system for hazardous conditions in mining environments by utilizing various technologies, such as Firebase, Flask, and HTML Web App. The web application developed using HTML, CSS, and JavaScript allows users to view sensor data in real-time. Data from the MQ7, DHT11, and MAX30102 sensors are visualized in graphs and tables that are easy to understand. This application is designed to facilitate users in monitoring environmental conditions and making decisions based on the available data.

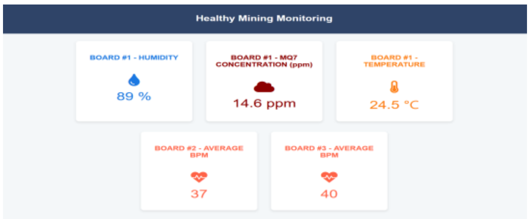

Figure 10 Web App Interface

The data retrieval speed from database was differently tested using the syntax “time_taken = end_time - start_time”, which calculates the time between the data request and data reception. The test results showed that the average time to retrieve data from Firebase is approximately 287 ms. This speed is crucial for applications that rely on real-time sensor data, ensuring that the system can respond to environmental changes in a timely manner.

Table 4 Response Time Test Result

Parameter	Definition	Test Results
Compression rate	MR for successful reconstruction	50-60%
Latency	Mean retrieval time	0.29 sec
Reconstruction accuracy	MAPE	0.047

V. Conclusion and Future Work

The integration of IoT technology with compressive sensing has proven to be an innovative solution for safety monitoring in underground mines. This technology overcomes key challenges such as bandwidth limitations, device power consumption, and extreme environmental conditions. By utilizing CS, data from multiple sensors can be efficiently compressed before being transmitted, reducing data transmission requirements without sacrificing accuracy.

In LOS conditions, the SF significantly impacts communication performance. At SF7, the average SNR 6.28 dB, and latency was 9.41 seconds. In contrast, SF12 showed slightly lower SNR at 4.01 dB, and increased latency to 12.92 seconds. Increasing SF from 7 to 12 enhances communication reliability but sacrifices data transmission efficiency and speed. Overall, SF7 is more effective for applications requiring fast data transmission and strong signals in NLOS scenarios.

The results indicate that the CS method with OMP effectively reconstructs signals close to the original, though performance varies by sensor type. Overall, CS demonstrates great potential for enhancing the efficiency of IoT systems in resource-constrained environments like underground mines.

To enhance system performance and reliability, the next phase of research should implement mesh networking and scheduling techniques. Mesh networking ensures scalability and robustness, maintaining continuous data flow even if some nodes fail. Together, these strategies will create a more efficient, reliable, and scalable IoT system, ensuring timely and efficient data transmission. The future implementation challenges may include the use of ruggedized sensors for environmental protection, adaptive sensing based on signal dynamics, and pre-determined sensing matrices to avoid repeated transmission of CS parameters.

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