



**DEVELOPMENT OF A GIS SYSTEM FOR MINING
DATA MANAGEMENT AND INTEGRATION FOR
PROACTIVE DECISION MAKING**

Master of Science (Dissertation)

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DECLARATION

I declare this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and this work has not been submitted for any other degree or professional qualification except as specified.



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October 30, 2024

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ABSTRACT

Mining activities serve as an imperative source of raw minerals and metals, playing a significant role in both industrial and domestic applications. However, these activities, among others, are also responsible for seismic incidents and rock bursts that can lead to serious injuries, lifelong disabilities, and the loss of lives among mineworkers. Annually, these incidents result in the casualties of approximately a thousand workers in subsurface mining operations.

In 2005, 203 people lost their lives in a mine accident in Sago, China. The following year, 17 people died in West Virginia, and in 2009, 73 people lost their lives in Gui Jiao, China. These tragic incidents underscore the urgent need for monitoring and management systems that can help mitigate the risks associated with such events. Therefore, enhancing occupational safety management standards and creating a safer working environment for mineworkers through effective monitoring is crucial.

To enhance mine safety, various research studies have proposed a digital dashboard application with innovative emerging data analytics and visualization capabilities. A digital dashboard is an intelligent communication system used to collect data from a network of multiple sensors, aiding in the near real-time monitoring, analysis, and visualization of data for underground mining operations.

This research study convincingly demonstrates the valuable sensor-based monitoring of the underground environment in near real-time, encompassing factors such as ground movement, ventilation, temperature, humidity, and toxic gases within the mining industry. These sensors continuously generate a bulk of

heterogeneous data, enabling management to identify trends and patterns that can inform planning and management decisions. The developed systems incorporate spatial modeling and analysis tools, providing assistance to quantify spatial and temporal processes, generate case scenarios, and enhance safety standards for mines.

Keywords: underground mines, GIS and RS, data integration, digital dashboard, centralized geodatabase, trends analysis, prediction analysis, warning alert, proactive decision making.

DEDICATION

To my teachers, who have imparted their knowledge and wisdom; to my parents, who have provided unwavering love and support; and to my friends, who have been there for me every step of the way. This work is dedicated to you all.

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TABLE OF CONTENTS

LIST OF FIGURES.....	9
LIST OF TABLES.....	10
LIST OF ACRONYMS.....	11
1. CHAPTER ONE - INTRODUCTION.....	12
1.1 Background	12
1.2 Research Problem Statement	16
1.3 Aim and Objectives	19
1.3.1 Aim	19
1.3.2 Objectives	19
1.4 Research Questions	19
1.5 Dissertation Structure	19
1.5.1 Chapter 1: Introduction	20
1.5.2 Chapter 2: Literature Review	20
1.5.3 Chapter 3: Materials	20
1.5.4 Chapter 4: Integrated Underground Mine Monitoring System..	20
1.5.5 Chapter 5: Results and Discussion	21
1.5.6 Chapter 6: Conclusions and Recommendations	21
2. CHAPTER TWO - LITERATURE REVIEW.....	22
2.1 Introduction	22
2.2 Underground Mining Environment	22
2.3 Mining Database Management.....	27
2.4 Underground Mining Safety in South Africa	37
2.5 Advantages of GIS Dashboards.....	40
2.6 Database and GIS integration	43
2.7 Use of GIS in the Underground Mining Cycle.....	45
2.8 Summary	48
3. CHAPTER THREE - MATERIALS	50
3.1 Introduction	50
3.2 Study Area.....	50
3.3 Monitoring Systems	53
3.3.1 Geo-technical Monitoring System	53
3.3.2 Ventilation System.....	59

3.3.3	Blast System	61
3.3.4	Weather Station.....	64
3.3.5	Mine Production Data	66
3.4	Data Summary	69
3.5	Summary	70
4.	CHAPTER FOUR - INTEGRATED UNDERGROUND MINE MONITORING SYSTEM.....	72
4.1	Introduction	72
4.2	Conceptualization of Monitoring System	72
4.3	Dynamic and Scalable System	72
4.4	Detailed Methodological Flow Chart.....	73
4.5	Data Collection	76
4.6	Centralized Geo-Database	78
4.7	Analysis	79
4.8	Visualization	82
4.9	Warning System	83
4.9.1	Climate KPI	84
4.9.2	Ground Movement.....	85
4.9.3	Gas Concentration	85
4.10	Summary	85
5.	CHAPTER FIVE - RESULTS AND DISCUSSION.....	86
5.1	Introduction	86
5.2	Centralized Geodatabase	87
5.3	Dashboards	89
5.3.1	Near real-time dashboard	92
5.3.2	Historic data dashboard	94
5.3.3	Forecasted data dashboard	95
5.4	Warning System	97
5.5	Summary	99
6.	CHAPTER SIX - CONCLUSION AND RECOMMENDATIONS	100
7.	REFERENCES.....	104

LIST OF FIGURES

Figure 1: Mining Companies use only a fraction of their data (Durrant-Whyte et al., 2015)	18
Figure 2: Simple service request processing (Castillejo et al., 2013)	32
Figure 3: Processing Unit (Faltpihl, 2012)	33
Figure 4: Trilateration method consisting of 3 beacon nodes and 1 tag node (Molapo et al., 2018b)	35
Figure 5: DT-based cyber physical architecture (Latsou et al., 2021)	39
Figure 6: Complaint Management System	43
Figure 7: Mining path Kurwi (2019)	47
Figure 8: Chamber of Mines building.	51
Figure 9: View Inside the Tunnel	52
Figure 10: Ground Movement Sensor on tunnel ceiling.	54
Figure 11: Strain gauge installed on the stope support.	55
Figure 12: Strain gauge installed on the ceiling in mock mine.	56
Figure 13: Detailed Methodological Flow Chart	74
Figure 14: Data Flow	76
Figure 15: Process Flow	77
Figure 16: Database Schema	79
Figure 17: Centralized Geo-Database viewed in PgAdmin.	89
Figure 18: Map on dashboard.	93
Figure 19: Near real-time dashboard	93
Figure 20: Historic data dashboard	95
Figure 21: Forecast data dashboard	97
Figure 22: Generated Mail by System	99

LIST OF TABLES

Table 1: Examples of database and GIS integration	46
Table 2: Starting and End Nodes of work.....	46
Table 3: Data Explanation	48
Table 4: Summary of Datasets	69

LIST OF ACRONYMS

KPI	Key Performance Indicator
GDP	Gross domestic product
GIS	Geographical Information System
GIN	Generalized Inverted Indexes
GST	Generalized Search Tree
API	Application Programming Interface
SQL	Structured Query Language
ISO	International Organization for Standardization
IDW	Inverse distance weighting
DSS	Decision Support Systems
WSN	Wireless Sensor Network
CPMS	Cyber Physical Manufacturing System
DT	Digital Twin
EBS	Enterprise Service Bus
RFID	Radio Frequency Identification
ORDBMS	Object Relational Database Management System

1. CHAPTER ONE - INTRODUCTION

1.1 Background

Underground mining plays a critical role in the global economy, contributing significantly to industrialization, employment, and resource extraction. It provides essential materials like coal, metals, and minerals that fuel various industries, from energy to technology. According to Zhironkin and Cehlár (2021), mining, particularly underground, continues to be a major contributor to the global economy, driving 29% of economic activity in the energy sector. Similarly, Shen and Gunson (2006) highlight that underground mining supports sustainable economic development, particularly in resource-rich countries like China, where it enhances both local and national economies by providing employment and increasing industrial output. Furthermore, Pavolová et al. (2022) emphasize the ongoing relevance of underground mining in Europe, where it maintains a vital position despite recent shifts towards sustainability in other industries. In terms of economic impact on South Africa, the mining industry accounted for a substantial R203.6 billion (South African Rand) in 2023, directly representing 7% of the Gross Domestic Product (GDP) (Statistics South Africa, 2023).

South Africa stands as a significant contributor to the world's mineral wealth, particularly through its vast reserves of gold-bearing conglomerates and platinum-bearing pyroxenites. These ore bodies extend several kilometers beneath the Earth's surface (Durrheim, 2010), underscoring their critical importance in the global supply chain of precious minerals.

Mineral and metal extraction operations, especially those involving underground mining, pose significant risks due to its hazardous nature. These risks include geological instabilities, equipment failures, and exposure to toxic gases. According to Ilyashov et al. (2019), gas contamination in underground workings increases the likelihood of accidents, while Kecojevic et al. (2008) highlight the high rates of fatal incidents related to continuous miners in U.S. mining operations. Sari (2002) also underscores the complexities of managing multiple risks, from equipment malfunctions to structural collapses in underground coal mines. Additionally, underground mining operations are associated with seismic events and rock bursts, contributing to the unfortunate annual toll of approximately a thousand casualties among mineworkers (Durrheim, 2010).

In response to these pressing concerns, the mining industry places paramount emphasis on safety measures and actively pursues the adoption of innovative modern technologies. These technologies leverage interoperability and harness the diverse range of critical professional skills within the industry to mitigate the inherent risks of subsurface mining. Moreover, the ongoing digital transformation in the mining sector has ushered in a significant influx of heterogeneous data. To fully harness the potential of this data for future risk mitigation, it is imperative to establish a centralized geodatabase for storage and analysis (Şalap et al., 2009).

The accumulation of substantial volumes of big data holds immense promise for enhancing mineral productivity and stands as a critical asset in the pursuit of a zero-harm approach to addressing social, environmental, and economic hazards within the mining industry. However, mining companies face a formidable challenge in harnessing the full potential of this vast data repository, which encompasses

information from geological, geographical, asset management, environmental, automation, mine production, geotechnical, mine waste, supply chain, and various other sources. The real challenge lies in the conversion of this extensive data set into intelligent, actionable information and knowledge that can yield valuable strategic insights. This transformation is crucial for effectively leveraging the wealth of generated data (Jonathan, 2004; Yanqing, 2019).

Numerous studies have explored the utility of database management systems in supporting the design, planning, and simulation of proposed mining activities (Katakwa, 2013). Additionally, research efforts have investigated the application of geospatial tools and techniques for analyzing both historical and contemporary data relevant to mining operations (Milner, 1997). Specifically, databases have served as repositories for comprehensive information about mining activities and associated facilities (Kopec, 2015).

The establishment of the Spatial Data Infrastructure (SDI) model has provided an integrated framework for various disaster management systems (Mansourian, 2006). This initiative has led to the development of web-based applications that leverage cognitive approaches to facilitate the sharing of critical information (Molina and Bayarri, 2011). These advancements reflect the industry's commitment to enhancing data-driven decision-making processes and bolstering overall safety and efficiency in mining operations.

The global demand for mineral resources continues to rise steadily, prompting mining companies to seek ways to maximize production, streamline operations, and enhance profitability. However, the geographical dispersion of mining activities and intricacies in the planning process often led to the emergence of 'functional

silos.' These silos can hinder efficient coordination and integration of various facets of mining operations, ultimately reducing mass production in mining activities (Tilton, 2014).

Moreover, the fragmentation of monitoring sensors, often sourced from different vendors, exacerbates the problem. Each sensor typically comes with its own separate monitoring dashboard. For example, the blast monitoring system may operate independently from the ventilation system, leading to situations where dust becomes suspended in the air following a blast, posing severe health risks to mineworkers. However, integrating both systems into a unified dashboard that considers the timing and intensity of blasts allows mine operators and managers to make informed decisions to adjust ventilation parameters promptly. This integration can also enable automation to expedite dust clearance, enhancing both worker safety and operational efficiency (Biffi and Belle, 2003).

It is well-established in the literature that a lowering of occupational safety management standards is directly correlated with an increase in the number of accidents (Sanmiquel et al., 2014). Recognizing the importance of elevating these standards and creating a safer working environment for mineworkers, effective monitoring becomes imperative. Addressing this issue, Horita et al. (2015) analyzed various research studies and proposed the development of a digital dashboard application equipped with innovative data analytics and visualization capabilities.

A digital dashboard serves as an intelligent communication system designed to gather data from a network of multiple sensors. It plays a pivotal role in monitoring, analyzing, and visualizing the collected data, facilitating near real-time management of underground mining operations (Atif et al., 2021). The outcomes

of this study underscore the significance of interactive and astute dashboards as essential components for enhancing the management of near real-time underground data insights. These dashboards empower mining professionals to make informed decisions, advancing the cause of intelligent and safe mining practices.

In this research study, the application of intelligent dashboards within the mining industry will be comprehensively explored, illustrating the significant benefits of sensor-based monitoring for various underground factors in near real-time. These factors include ground movement, ventilation, temperature, humidity, and toxic gases such as carbon monoxide. Despite the mining industry's consistent generation of vast and diverse datasets, this research aims to showcase how these intelligent dashboards can be instrumental in identifying trends and patterns, thereby enhancing planning and management decision-making processes.

Within these developed systems, the integration of spatial modeling and analysis tools emerges as an asset. These tools facilitate the quantification of spatial and temporal processes, enabling the generation of diverse case scenarios (Groffman, 2009). Ultimately, this approach significantly contributes to the elevation of safety standards within mining operations, as emphasized by prior research (Şalap et al., 2009).

1.2 Research Problem Statement

Accidents in underground mines pose severe consequences, including serious injuries, lifelong disabilities, loss of life among mineworkers, and significant disruptions to production, leading to substantial economic losses for mining companies. For instance, the tragic incident in Sago, China, in 2005 resulted in the loss of 203 lives. West Virginia witnessed 17 fatalities in a mining accident in 2006,

and Gui Jiao, China, experienced a devastating loss of 73 lives in 2009 (Zheng et al., 2009). In 2021, the fatal injury rate for the mining industry as a whole was 14.2 per 100,000 full-time equivalent workers (Mining Fatalities Rose 21.8 Percent From 2020 to 2021, 2023). As of 2023 South African mining industry reported a total of 54 fatalities during the year (Mining Industry Fatalities in South Africa From 2000 to 2023, 2024). These distressing incidents underscore the critical need for robust monitoring and management systems capable of mitigating the risks associated with mining operations.

Remarkably, during the operation of mines, an extensive volume of data is collected, which possesses significant potential for informing safer and more efficient mining practices. However, it is disheartening to note that less than 1% of this valuable data is effectively utilized in the decision-making process. Several factors contribute to this underutilization: data may not be stored due to inadequate infrastructure, it may remain inaccessible due to flawed data management practices, or it may go unanalyzed and uncommunicated to decision-makers. Even when this data reaches the hands of those responsible for decision-making, it often remains underutilized, as illustrated in **Figure 1** (Durrant-Whyte et al., 2015). Addressing these data challenges is paramount for advancing safety and efficiency in mining operations.

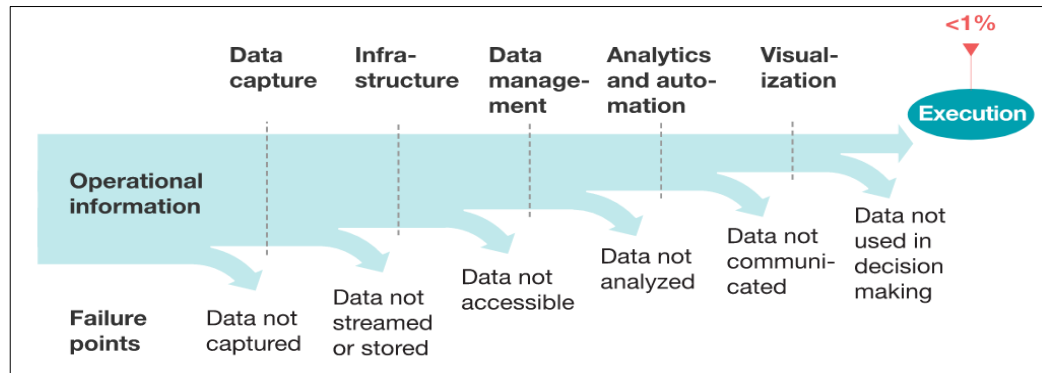


Figure 1: Mining Companies use only a fraction of their data (Durrant-Whyte et al., 2015)

It is evident that there is a critical need for greater utilization of operational information in the decision-making process to enhance both the productivity and safety of mining operations. Geographic Information Systems (GIS) stand out as a dynamic platform capable of facilitating near real-time visualization and analysis of the world (Lü et al., 2018). While the application of GIS has proven highly effective in mining contexts, it is notable that there is a scarcity of systems specifically designed for mine monitoring and management using GIS (Choi et al., 2020).

In response to this gap, the focus of this research endeavor is the development of an integrated near real-time dashboard. This dashboard will serve as a centralized hub for the analysis and visualization of critical operational data within mining operations. By harnessing GIS capabilities, this system will empower mining professionals to make proactive and data-driven decisions, ultimately contributing to improved safety and productivity within the mining industry.

1.3 Aim and Objectives

1.3.1 Aim

This research aims to develop a GIS-based integrated system for individual mine monitoring systems. This system will aid in the visualization of collective data in context with each other, facilitating proactive decision-making.

1.3.2 Objectives

The main objectives of the research are:

1. Development of a centralized geodatabase for seamless and near real-time data integration from multiple systems in a mining environment.
2. Application of mining analytics for risk management using Key Performance Indicators KPIs.
3. Development of a comprehensive GIS system to visualize and analyze different parameters in relation to each other for proactive decision making

1.4 Research Questions

As part of the research, following are questions that need to be focused:

1. Can PostgreSQL effectively store and serve data for near real-time monitoring from multiple sources?
2. What relationships exist between different parameters in an underground mining environment?
3. Can GIS be effectively applied to an underground mining environment?

1.5 Dissertation Structure

This thesis comprises six chapters outlined:

1.5.1 Chapter 1: Introduction

Chapter 1 introduces the research, addressing the issue of mining accidents, emphasizing the importance of the research. It highlights challenges posed by isolated monitoring systems, defines the problem statement, outlines objectives, and formulates research questions.

1.5.2 Chapter 2: Literature Review

Chapter 2 reviews Geographic Information Systems (GIS) in the mining industry, exploring their advantages and limitations. It investigates technologies for establishing an integrated GIS system for underground mine monitoring and an early warning system, drawing insights from integration technologies in various sectors.

1.5.3 Chapter 3: Materials

Chapter 3 comprehensively discusses the infrastructure of the study area (DigiMine), including its surface control room and underground mock-up mine. It highlights the purpose of DigiMine in fostering innovation, research, and development by bridging surface digital technologies with the underground mining environment.

1.5.4 Chapter 4: Integrated Underground Mine Monitoring System

Chapter 4 serves as the core of this dissertation, presenting the data sources, methodologies, and techniques adopted for integrating data and constructing the integrated monitoring platform. This chapter outlines the development of a warning system, which plays a pivotal role in generating alerts for relevant authorities.

1.5.5 Chapter 5: Results and Discussion

Chapter 5 presents the culmination of the research efforts, highlighting the development and features of the integrated GIS-based monitoring system. The chapter delves into the outcomes, specifically the creation of dashboards that serve as a visual representation of the collected data.

1.5.6 Chapter 6: Conclusions and Recommendations

Chapter 6 synthesizes the implications of the resultant dashboards and their potential impact. Additionally, it offers insights into avenues for future work, highlighting opportunities to further enhance the system's capabilities and ultimately contribute to the establishment of safer underground mining environments.

2. CHAPTER TWO - LITERATURE REVIEW

2.1 Introduction

This chapter comprehensively reviews existing literature related to key aspects of the underground mining environment. It explores underground mining databases, safety measures in South African mining operations, and the utilization of Geographic Information Systems (GIS) throughout the underground mining cycle. The discussion also encompasses various GIS systems tailored for mining applications and data management strategies. Relevant articles and scholarly journals are highlighted to offer essential insights, elucidating the methodology and rationale behind developing a GIS system for underground mine monitoring. This literature review establishes a foundational basis for the subsequent chapters, framing the research within the broader context of existing knowledge and best practices.

2.2 Underground Mining Environment

In intricate mining operations, the vigilance and oversight of all integral systems are imperative to ensure the safety and functionality of the mine. This holds particular significance within the mining industry, where the absence of comprehensive monitoring can exacerbate inherent hazards. Among these systems, ventilation systems assume a paramount role in safeguarding mine workers and facilitating normal operational conditions, as the absence of proper ventilation can render mining endeavors exceedingly challenging. Prudent mine planning is an essential precursor to commencing mining operations.

Notably, Nikolaskis et al. (2021) pioneered the development of a cyber-physical system designed to enable on-demand ventilation control within mining environments. This system relies on physical sensors and a centralized infrastructure for ventilation control. The research conducted by Nikolaskis, and colleagues culminated in a significant finding: the integration of sensor-based monitoring systems tailored to underground mine conditions holds the potential to substantially enhance decision-making processes. Geographic Information Systems (GIS) emerge as a pivotal tool in this context, offering multifaceted contributions, including the optimization of mine planning, the refinement of mining processes, and the assessment of environmental impact within mining locales.

In the realm of mining operations, the integration of Geographic Information Systems (GIS) holds profound implications for the optimization of mine planning, process enhancement, and environmental conservation assessments. Furthermore, the vital facet of database management warrants discussion in this context. Database management within mining operations entails the utilization of the Python programming language, commonly referred to as scripting, while GIS systems serve as the bedrock for housing and processing scientific data, predominantly relying on the Python language and PostgreSQL database.

In the context of mining data administration, it is imperative to manage georeferenced, three-dimensional, and attribute data formats efficiently. Mine-related data encompass a wide spectrum, encompassing crucial elements such as drill holes, ore bodies, inert deposits, pit boundaries, and ancillary transport networks, which exhibit distinctive spatial characteristics. The GIS environment

offers a comprehensive framework for the storage, manipulation, and management of this multidimensional dataset.

This approach entails the representation of mine data in georeferenced formats, wherein geographic coordinates are intricately linked with specific spatial features. Furthermore, the incorporation of longitudinal information, encompassing precise locational details, and attribute data, detailing the spatial properties of elements within the mining environment, facilitates a holistic understanding of the mining landscape.

In the context of mining operations, this methodology has proven particularly pertinent for a range of applications, including the storage and management of drill hole data, which plays a pivotal role in mining exploration and resource assessment. Furthermore, GIS systems have demonstrated their utility in the representation of block models for inorganic deposits, the intricate mapping of underground transportation networks, the monitoring of underground environmental attributes through the deployment of ZigBee nodes, and the optimization of underground ventilation networks.

This multifaceted approach underpins the transformation of raw mining data into actionable insights, facilitating informed decision-making processes, and contributing significantly to the overall efficiency, safety, and sustainability of mining operations. In tandem with data science, various specialized packages, such as NumPy, have gained widespread recognition and extensive usage within the mining community, further augmenting the analytical capabilities available for scientific investigations and mining endeavors.

Geographic Information Systems (GIS) emerge as formidable tools offering substantial support for decision-making across various stages of mining development. These applications encompass critical facets of the mining lifecycle, including ore reserve exploration and estimation facilitated by spatial 3D query tools. Additionally, GIS facilitates the visualization of uncertainties within open-pit boundaries and aids in land-use planning post-mine closure through comprehensive multi-criteria decision analysis.

Moreover, the utility of GIS extends to the proactive identification of potential mining-induced conflicts, accidents, and risks through advanced spatial analysis tools. By harnessing the capabilities of enterprise GIS technology, the wealth of data and information generated during mining operations can be seamlessly shared among stakeholders, fostering collaborative discussions that underpin the identification of optimal decisions.

Park et al. (2020). conducted a notable study involving the measurement of carbon dioxide emissions from diesel vehicles operating within an underground mine, employing GIS as a pivotal component of their research methodology. A dedicated GIS database was established to facilitate data management specific to underground mining operations.

In this study, the average travel speed of diesel vehicles along various routes was meticulously estimated through extensive field surveys. This data served as a foundational basis for calculating the carbon dioxide release factor. Notably, these vehicles are integral to mining operations, and data collection was undertaken in a systematic manner for subsequent management within the database management system.

This exemplifies the power of GIS in the rigorous quantification and analysis of environmental impacts within the mining industry. The integration of GIS technology allows for precise measurements and informed decision-making to mitigate the ecological footprint of mining activities, underscoring the multifaceted role of GIS in fostering sustainability within mining operations.

The study conducted by Park et al. (2020) unearthed critical insights into the quantification and management of carbon dioxide emissions associated with truck operations within an underground mining context. The study harnessed the power of Geographic Information Systems (GIS) and network analysis, offering a comprehensive and data-driven approach to proactive decision-making.

One of the pivotal findings of the research revolved around the ability to estimate carbon dioxide emissions by considering the carbon dioxide emission factor with the travel distance of diesel vehicles. This GIS-based network analysis and integration served as an invaluable tool for refining decision-making processes about truck operations within the mining environment.

However, it is imperative to acknowledge certain limitations within the study. Specifically, the research did not delve into the variability of the carbon dioxide emission factor across different roads, which can be influenced by factors such as road gradient. Such variations have far-reaching implications, encompassing environmental impact, the load-bearing capacity of vehicles, and compliance with emission standards. These variables, which were not explored in depth within this study, warrant further consideration in future investigations.

This study underscores the intricate and multifaceted nature of environmental management within the mining industry. It highlights the potential for GIS-based analyses to inform decision-making processes, but it also emphasizes the need for a holistic approach that considers a broader spectrum of variables to achieve comprehensive and sustainable solutions.

2.3 Mining Database Management

PostgreSQL, an Object-Relational Database Management System (ORDBMS), leverages the capabilities of the PostGIS extension to enhance its geospatial functionalities. PostGIS augments PostgreSQL with an extensive library encompassing over a thousand geo-spatial functions and a suite of spatial operators tailored for geospatial measurements, encompassing parameters like area, distance, length, and perimeter.

The integration of GiST (Generalized Search Tree) indexes within PostgreSQL significantly bolsters its ability to execute high-speed spatial queries. This indexing mechanism empowers PostgreSQL to retrieve geospatial data swiftly and accurately, rendering it a stalwart choice for applications demanding real-time geospatial querying.

The synergy between PostgreSQL and PostGIS propels it to the forefront of integrated systems featuring a geo-spatial component. This offers the most extensive library of spatial functions available, cementing its position as the preferred choice for robust geospatial data management.

In a comprehensive performance benchmarking study conducted by Makris et al. (2020), PostgreSQL emerged as the clear victor when pitted against the NoSQL

database MongoDB. The benchmark tests were meticulously designed to mirror real-world scenarios, encompassing a diverse array of spatial queries.

The standout result of this comparison was PostgreSQL's consistently superior performance, boasting lower response times across nearly all categories of spatial queries. This underscores PostgreSQL's capability in handling complex geospatial data, making it the preferred database system for applications reliant on fast and accurate geospatial analysis.

PostgreSQL, fortified by the capabilities of PostGIS, not only empowers practitioners with an expansive arsenal of geospatial tools but also outshines rival database systems when subjected to rigorous real-world testing, making it the preeminent choice for geospatial data management and analysis.

In the context of a GIS system designed for mining data management, "environmental risk factors" pertain to the conceivable adverse effects on the environment stemming from mining operations. These risk factors encompass a range of potential hazards, such as soil and water contamination, deforestation, and the disruption of wildlife habitats.

Incorporating data and analyses pertaining to environmental impacts within the data management and integration processes of the GIS system assumes paramount importance. This inclusion facilitates an in-depth assessment of the environmental ramifications associated with mining activities. Such insights empower decision-makers to gain a comprehensive understanding of the potential repercussions of their choices, enabling them to make well-informed decisions geared towards mitigating and minimizing adverse environmental consequences.

Finally, observing the system involves regularly monitoring its performance and usage, and making any necessary adjustments to ensure it continues to meet the needs of the mining industry and support proactive decision-making. These adjustments encompass a spectrum of actions, such as updating data and analyses, refining tools and interfaces, and addressing any technical or operational challenges that may emerge.

In recent times, Python has witnessed a surge in popularity among data scientists and developers, as noted by Robinson in 2019. Python, characterized as a scripting language, differs from languages that are compiled into binaries before execution. Instead, Python employs a real-time language interpreter for on-the-fly execution, a process known for its relative slowness. But Python has garnered widespread acceptance in the realms of analysis and data science, largely due to the availability of key packages that enjoy robust community support and widespread usage.

Notable among these packages is NumPy, recognized as the foundational package for numerical computations in Python. Complementing NumPy is SciPy, an advanced package building upon NumPy's capabilities for scientific computations. Pandas, another widely embraced package, offers enhanced tools for data structure manipulation and analysis. For visualization, matplotlib provides valuable capabilities within the Python ecosystem. Moreover, Scikit-learn, boasting a comprehensive library of machine learning algorithms, further enriches Python's utility in data management and analysis, as highlighted by Hao and Ho in 2019.

Nelson et al. (2007). employed Geographic Information System (GIS) software and a systematic methodology to investigate gradient failures within the Chuquicamata open pit mine. Their investigation encompassed several key stages, commencing

with the initial compilation and preparation of data, followed by a rigorous process of data validation, the creation of derivative data layers, and ultimately, developing predictive models. Moreover, the assessment of slope failure risk was conducted by comparing GIS-based predictive models for slope stability with actual slope failures observed post-modeling.

The outcomes of this comprehensive approach demonstrated the superior efficacy of GIS-based modeling methods when compared to conventional graphic-based drawing programs for assessing the risk of slope failure in an open-pit mining context. This underscores the significance of leveraging GIS technology in geotechnical assessments, as it offers a more robust and data-driven framework for evaluating slope stability and the mitigation of potential risks within mining operations.

An exhaustive review of 58 recent articles dedicated to GIS-based applications in mining has unequivocally underscored the robustness and versatility of Geographic Information Systems (GIS) as a formidable tool in various facets of mine development. GIS emerges as a pivotal asset for the planning, design, and enhancement of diverse stages within the mining domain. Furthermore, it proves invaluable in the realm of mine spatial data management, thereby enhancing the development of decision-support systems that facilitate informed and efficient decision-making..

The efficacy of GIS becomes pronounced when multiple parameters need to be considered concurrently, as elucidated in the study by Choi et al. in 2020. The multifaceted capabilities of GIS empower mining professionals to navigate complex terrain, optimize processes and enhancing overall operational efficiency.

Shifting the focus to the underground environment and the well-being of mineworkers, research conducted by Sunkpal et al. (2017) delved into the assessment of thermal comfort levels in accordance with the ISO 7933 thermal limit criteria. Employing MATLAB and leveraging thermal model equations, a mathematical model was meticulously crafted to formulate indices that gauged thermal conditions. These indices were predicated upon critical parameters, such as maximum sweat and skin wetness criteria. Notably, this endeavor extended to predicting boundary limits within a temperature range spanning from 10°C to 50°C, coupled with other dynamic parameters. Such research endeavors epitomize the commitment to ensuring the well-being and safety of mineworkers, underpinning the imperative role of scientific analysis in this critical domain.

A wearable device was developed which can store or transmit Physiological data about the wearers body via Bluetooth in real-time. This device interfaces with an operator subsystem consisting of an Enterprise Service Bus (ESB), a personal computer (PC), and a base station. Within this subsystem, data management and coordination are orchestrated by the ESB, built upon the open-source Fuse ESB software, which relies on Apache Service Mix and adheres to the Service-Oriented Architecture (SOA) model. Accessibility to service data is facilitated via REST APIs, permitting users to make data requests from various devices, including smartphones and personal computers. The operator subsystem additionally features alarm configuration for timely response to critical events.

Concurrently, the Body Area Network Subsystem governs the integration of wearable devices. Users are equipped with a Zephyr belt and two SunSPOT motes, one functioning as a monitoring node and the other as a bridge node. The

monitoring node collects data from SunSPOT nodes responsible for temperature data, while the bridge node establishes a Bluetooth connection with the Zephyr belt to facilitate data transmission to the monitoring node. This intricate network design enables seamless integration of wearable devices, enabling real-time data collection and analysis, with potential applications in fields such as health monitoring and safety enhancement. **Figure 2** shows the processing of a simple service request.

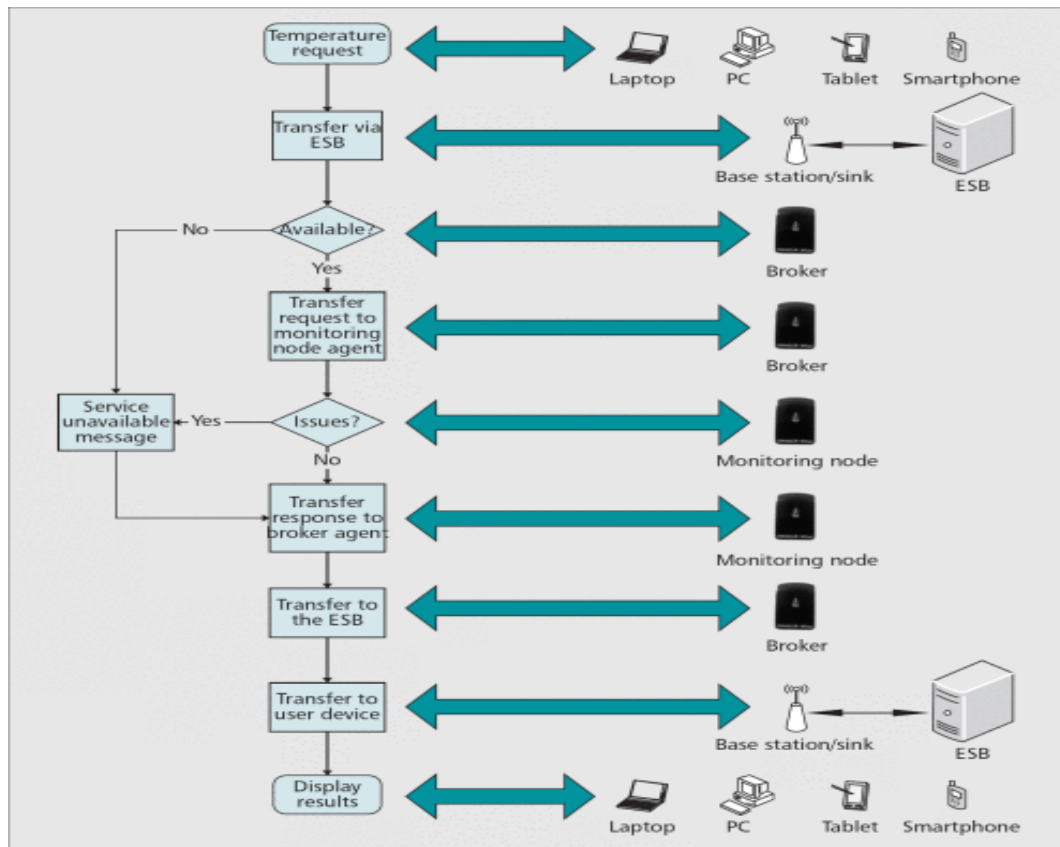


Figure 2: Simple service request processing (Castillejo et al., 2013)

In their study, Sung and Hsu (2013) harnessed the versatile FLAG-PSoC platform, a programmable System-on-Chip (SoC) platform capable of seamlessly integrating diverse modules. Their research centered on leveraging the capabilities of the FLAG-PSoC platform to merge a ZigBee wireless network with temperature sensors and accelerometers, thereby creating a unified system for environment

monitoring. This innovative approach allowed for the effective surveillance of environmental conditions and the collection of data for research and analysis purposes. Components are shown in **Figure 3**.

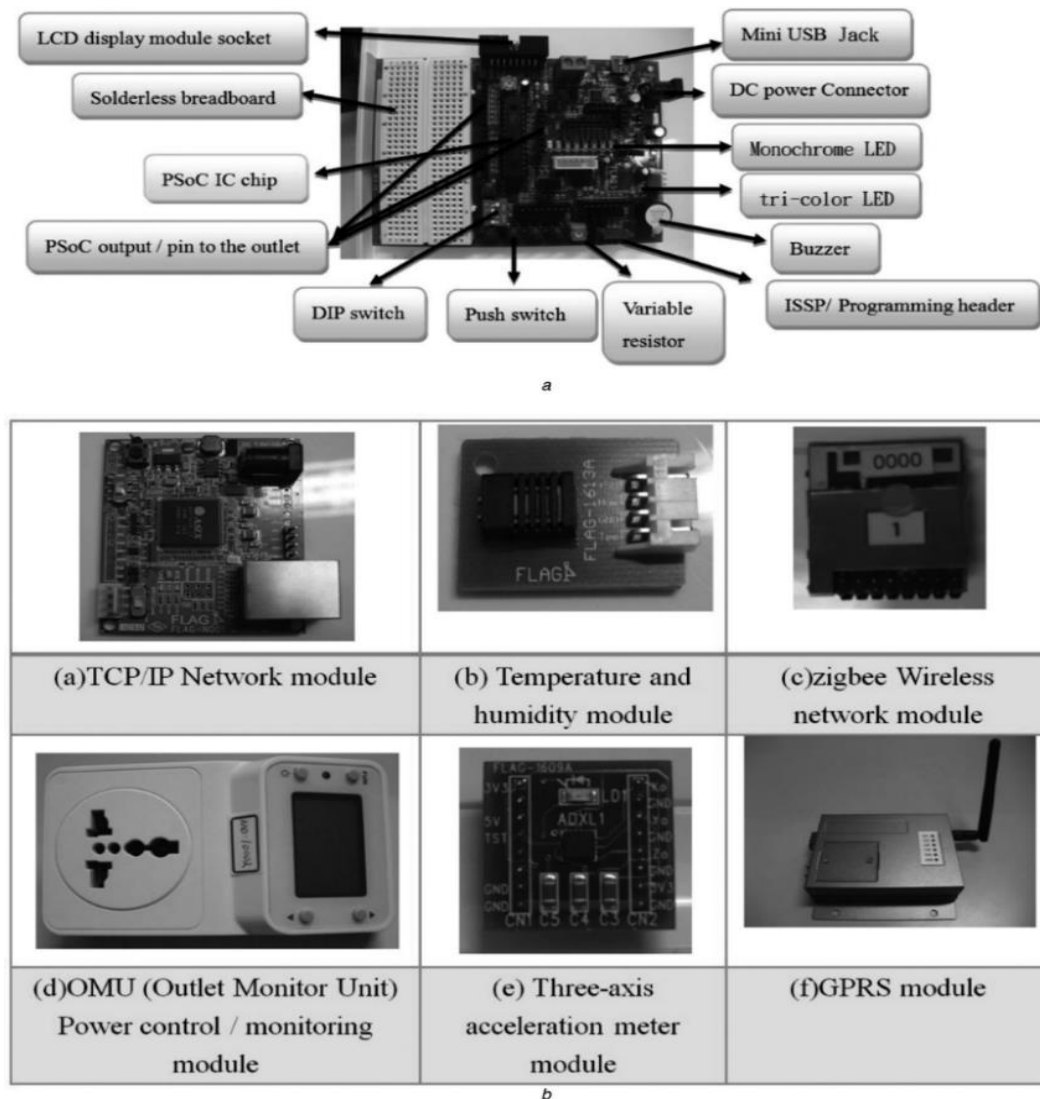


Figure 3: Processing Unit (Faltpihl, 2012)

Molapo et al. (2018) executed a noteworthy implementation involving a Wireless Sensor Network (WSN) designed for the real-time monitoring of livestock. In this deployment, a network of beacons was strategically positioned across the fields,

while individual tags were affixed to the livestock. The researchers employed the trilateration method to precisely locate each tag within the network.

The trilateration method, adopted for this purpose, relies on signal strength measurements to calculate the distances between the tags and the beacons. These beacons are interlinked with a base station via the WSN infrastructure, facilitating the seamless transmission of data. This data, collected by the beacons, is provided for analysis at the base station, enabling the visualization of the real-time positions of the monitored livestock.

The determination of the location involves a two-tiered approach. Firstly, the location is localized based on the known positions of the beacons. Subsequently, this localized position can be referenced on a global scale. Alternatively, the localized location can be utilized as is, depending on the specific requirements of the monitoring application. For clarity, **Figure 4** illustrates the trilateration method employed to calculate the precise location of a tag by leveraging data from three strategically positioned beacons.

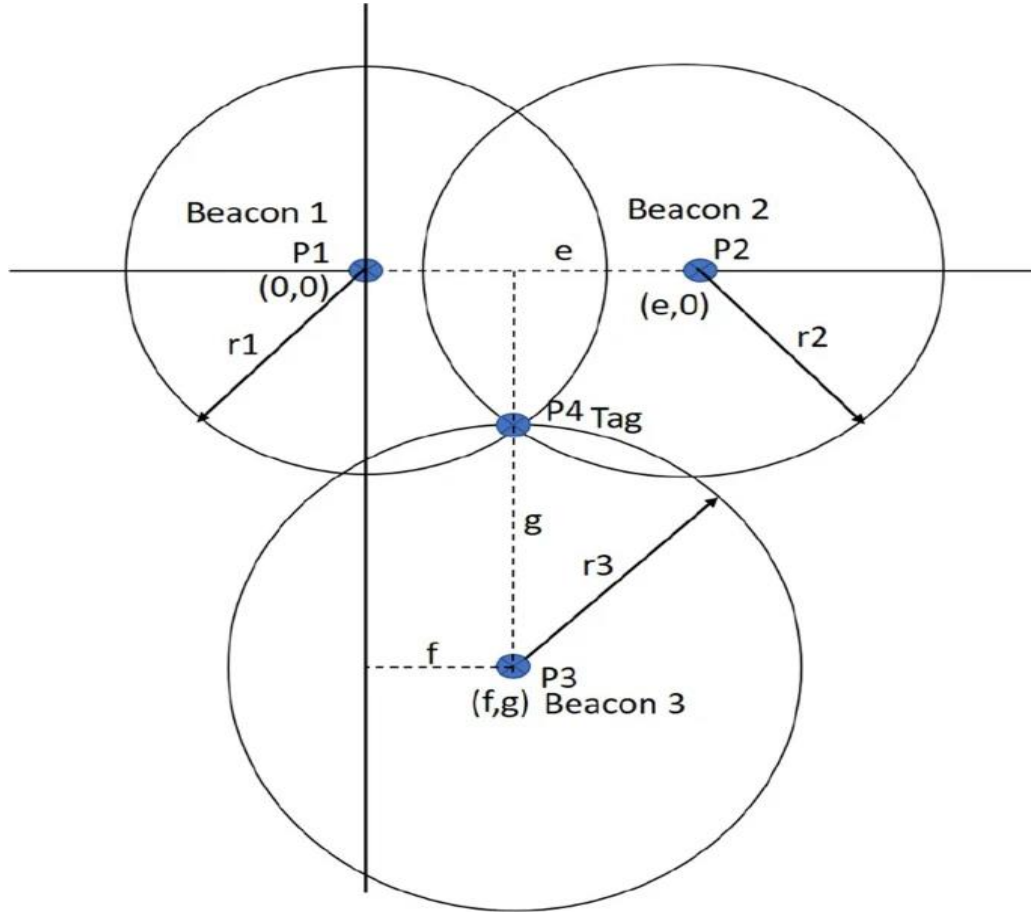


Figure 4: Trilateration method consisting of 3 beacon nodes and 1 tag node

(Molapo et al., 2018b)

In their research, Latsou et al. (2021) adeptly implemented a Digital Twin (DT) architecture within the context of a complex manufacturing system, wherein multiple agents-based Cyber-Physical Manufacturing System (CPMS) played a pivotal role. The development of the DT-CPMS system was underpinned by a well-established five-layer architecture, which draws inspiration from the Internet of Things (IoT) paradigm.

Smart Connection Layer consists of the physical components including Human Resources, Equipment, material resources and RFID Hardware. Conversion Layer consists of the physical data that is collected from the RFID Equipment or Human

Inputs. The Cyber layer consists of the Network components which connects this data to the next Layer. Cognition layer contains all the Knowledge base. This knowledge base is utilized by the configuration layer to provide services such as data analytics, predictive analysis, Scenarios analysis and optimization.

This five-layer architecture consists of the following integral layers:

Smart Connection Layer: This foundational layer encompasses the physical components essential to the manufacturing process. It comprises Human Resources, Equipment, Material Resources, and RFID Hardware, which are integral to the system's operation.

Conversion Layer: The Conversion Layer handles the physical data acquired from RFID Equipment or through Human Inputs. It serves as the bridge between raw data and subsequent processing stages.

Cyber Layer: At the core of this architecture lies the Cyber Layer, housing the network components that facilitate the seamless transmission of data from the Conversion Layer to the subsequent layers. This layer forms the backbone of the digital ecosystem.

Cognition Layer: The Cognition Layer serves as the repository of knowledge. It encompasses a comprehensive knowledge base, which is harnessed by the system's Configuration Layer to provide a range of services. These services encompass data analytics, predictive analysis, scenario analysis, and optimization, which are crucial for informed decision-making.

Configuration Layer: The Configuration Layer utilizes the knowledge base stored in the Cognition Layer to deliver a spectrum of valuable services. These services

are indispensable for optimizing system performance, facilitating data-driven insights, and enhancing overall operational efficiency.

This meticulously designed five-layer architecture underpins the DT-CPMS system, offering a robust and structured framework for the integration of physical and digital components within the manufacturing ecosystem.

2.4 Underground Mining Safety in South Africa

In the context of underground mining safety in South Africa, Geographic Information Systems (GIS) have emerged as a powerful tool for the storage, retrieval, transformation, and visualization of spatial data derived from the real world. This technology has found significant application in the mining sector, particularly in South Africa, where diverse mining techniques are employed to enhance both the mining process and the well-being of workers.

Mallya et al. (2001) have diligently crafted a GIS framework that encompasses the entire spectrum of coal mining activities, spanning from initial planning stages to on-site mining operations. This structured framework not only streamlines the decision-making process but also serves as a Decision Support System (DSS), facilitating the monitoring of activities within mining operations (Mallya et al., 2001). The integration of advanced technologies has become a prevalent practice in various industries across Africa, enhancing operational efficiency and monitoring capabilities.

Furthermore, Castillejo et al. (2013) have exemplified the integration of Wireless Sensor Networks (WSN) and the Internet of Things (IoT) within the context of E-Health and physiological monitoring. In their research, they have developed and

implemented an application equipped with real sensors to monitor sports performance, demonstrating the practical application of advanced technologies for real-time monitoring in diverse contexts.

In the research conducted by Castillejo et al. (2013), an important challenge highlighted in using Wireless Sensor Networks (WSN) was the divergence in communication protocols and standards among the sensors. This divergence meant that some wireless sensors relied on IEEE 802.15.4, while others utilized Zigbee, and still, others employed Bluetooth for communication. To ensure seamless integration of these sensors, it was imperative to address these disparities in communication standards comprehensively.

Prakash and Vekerdy (2004) developed Coal-Man, a GIS utilized in China for monitoring coal mine fires. This system, constructed with ILWIS and complemented by GIS packages, consists of four key components: a Database, Data Management, Data Analysis, and Data Visualization tools. Coal-Man offers the capability to detect and map coal fire areas, monitor fires over time, classify fires based on characteristics, identify vulnerable areas, and create action plans for firefighting. In simplifying the interaction with GIS for decision-makers, the emphasis is placed on understanding how to input data and visualize information (Prakash & Vekerdy, 2004). Additionally, the integration of GIS with sensor web service platforms can enable real-time environmental data monitoring (Gong et al., 2015).

A simulation model has been developed to effectively utilize the collected data and simulate system behaviors. The outcomes of these simulations can be leveraged to enhance system performance. Furthermore, these services can be activated by the

physical layer to further optimize system performance. This system was successfully implemented within a cryogenic warehouse facility. The intricate cryogenic manufacturing process involves primary manufacturing, storage, and ultimately serving the end consumer. The manufacturing phase requires significant manual labor at various stages, leading to potential inefficiencies. To address these challenges, the digital twin's monitoring capabilities were harnessed, allowing for the refinement of processes based on model simulations (Latsou et al., 2021), as illustrated in **Figure 5**.

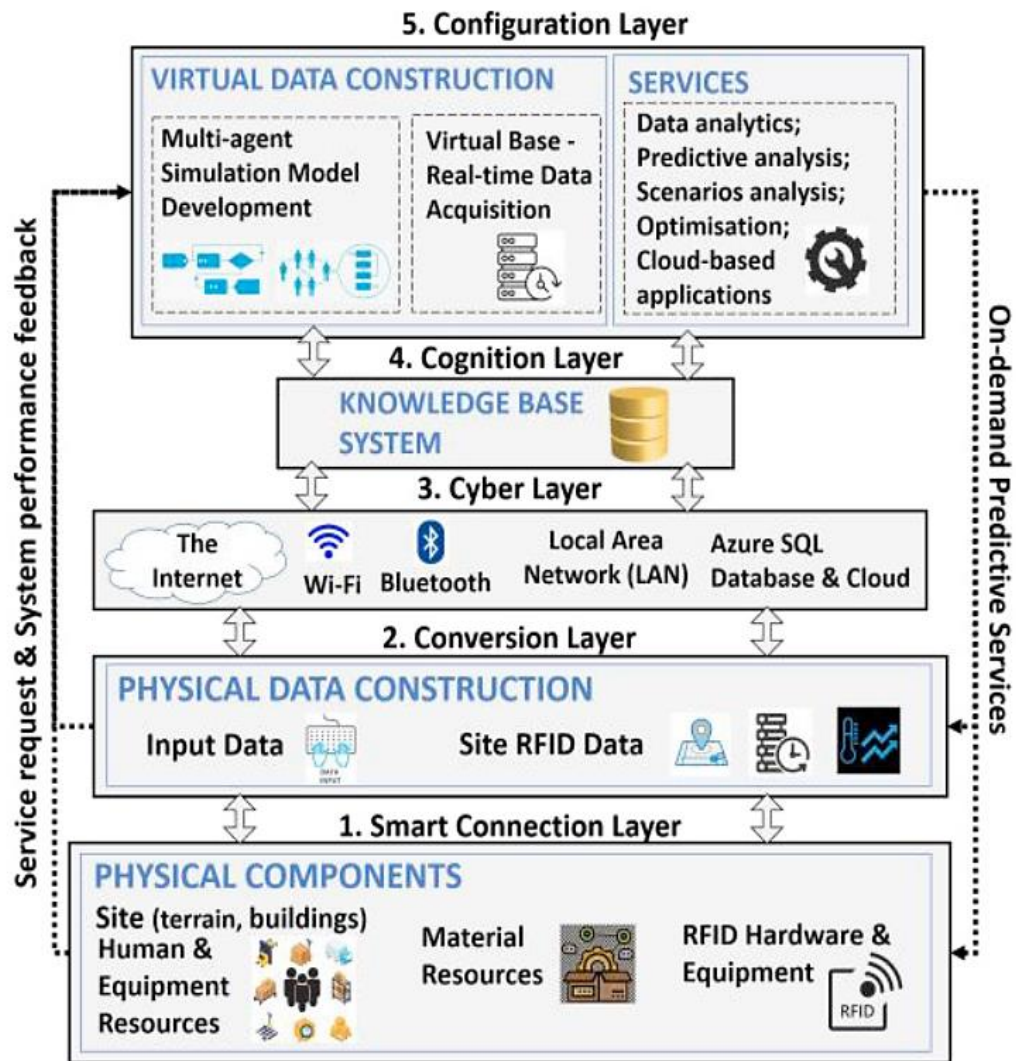


Figure 5: DT-based cyber physical architecture (Latsou et al., 2021)

2.5 Advantages of GIS Dashboards

Dashboards offer several advantages, notably enhancing data clarity and enabling organizations to gain deeper insights. However, the market is saturated with numerous tools and software options for creating dashboards. Selecting the right data visualization tool can be a daunting task, as many platforms offer similar core functionalities, but each specializes in specific commercial use cases. The choice of the appropriate tool holds significant importance for an organization's long-term success, especially given the challenges associated with altering the core components of data analytics mid-project (Sigdel, 2022).

Miller (2021) highlights the value of GIS dashboards, emphasizing their capacity to empower operators by offering location-based analytics through intuitive and interactive data visualization on a single screen. Organizations leveraging GIS platforms can harness GIS dashboards to facilitate decision-making, visualize trends, monitor real-time status, and update various teams. These dashboards can be customized to cater to specific audiences, enabling them to share information and obtain the answers they require. Dashboards are a crucial product for sharing information, including maps and applications, and play a pivotal role in enhancing your geospatial infrastructure. A GIS dashboard serves as a tool for capturing and analyzing geographically referenced data. In this context, it processes data linked to a specific location and analyzes spatial data, enabling stakeholders to explore maps and uncover hidden geographical patterns. Ultimately, GIS serves as a dynamic solution for organizations, cities, and nations.

At the process level, the integration of a database and GIS does not alter the data format and structure. To overcome this challenge, reference ontologies, as part of

the Semantic Web or Web Service, are employed to enhance the potential of cross-domain architecture mapping, facilitating the storage and presentation of object differences. For instance, Rosse and Mejino (2003) utilized the Foundational Model of Anatomy (FMA) as a reference ontology to establish correlations among various biomedical informatics perspectives. Then detailed, and expressive ontologies, coupled with semantic web technologies, were applied to integrate GIS, Building Information Modeling (BIM), and a range of infrastructure systems, including smart metering, wastewater management, and scientific water supply networks.

A automated method model has been developed using semantic network technology to consolidate data related to significant landscape highway routes. These semantic web technologies play a crucial role in addressing data interoperability challenges and partially meeting the data requirements for community energy design. However, there are ongoing challenges associated with leveraging semantic web technologies, including the Web Ontology Language (OWL) and Resource Description Framework (RDF). The absence of a standardized ontology and mandatory information base remains a key challenge in this domain.

According to Miller (2021), using the Dashboard for ArcGIS offers the advantage of enabling even non-programmers to create feature-rich, customized dashboards in a shorter amount of time. A dashboard is constructed by combining various elements or widgets, each of which serves as a building block for the dashboard. The application provides a range of widgets, such as home, zoom in and out, legend, pie chart, graph, map, indicator, gauge, list, and feature, among others.

Operators have the flexibility to customize widgets, defining their appearance and placement within the dashboard. Operators can establish how widgets interact with

one another. For instance, when a specific region is selected from a list of regions, the corresponding geographic area is displayed on the map. Common actions associated with widgets include sorting, arranging, duplicating, and deleting, among others. The application is designed with a responsive approach, ensuring that it functions correctly on devices with varying screen sizes. This adaptability allows for a seamless user experience regardless of the device being used.

Interactive dashboards that leverage sensor data from mines and present it in an interactive manner have proven invaluable for enhancing the decision-making process. Atif et al. (2021) utilized Tableau to create advanced and intelligent dashboards that establish live connections to sensor data, providing real-time insights and facilitating informed decision-making.

To ensure safer mining operations and safeguard the health of mine workers, a health monitoring system was developed to continuously assess the well-being of laborers in the mine. Advanced technologies were employed to collect and analyze data, harnessing Artificial Intelligence and Machine Learning algorithms. The results were then utilized to provide personalized health recommendations to mine workers (Madahana et al., 2020). Monitoring and communication within the underground mining environment plays a pivotal role in safeguarding mining assets and ensuring the safety of personnel (Suganthi et al., 2021). These critical aspects of mine management are essential for mitigating risks and protecting both human and economic resources.

Zeiler (1999) highlighted the significant advantages offered by GIS Dashboards, emphasizing their capacity to expedite decision-making and enable real-time monitoring of various facilities, properties, and functions through a unified

interface. This capacity to provide consolidated and up-to-date information on a single screen stands out as a crucial benefit of GIS dashboards.

In GIS-based research for mining data, the planning process typically encompasses four key areas: mineral reserve estimation, optimization of open-pit mining operations, design of pit layouts, and analysis of potential conflict areas.

Zeiler (1999) emphasized the user-friendliness of GIS dashboards. These dashboards excel in presenting data in a highly comprehensible format, allowing users to access all pertinent facts and figures on a single screen. This streamlined presentation greatly enhances the speed and simplicity of data comprehension, as exemplified in **Figure 6**.



Figure 6: Complaint Management System (ArcGIS Dashboards | Data Dashboards: Operational, Strategic, Tactical, Informational, n.d.)

2.6 Database and GIS integration

The Fourth Industrial Revolution has ushered in an era characterized by the relentless acquisition of copious amounts of data. This influx of data has rendered big data analysis an invaluable resource across diverse professional domains. One

such application of significant import is the practice of data mining, particularly when employed in time series analysis. Time series analysis offers the capability to discern temporal trends and patterns within datasets, enabling the prediction of future trends for a given object or phenomenon. This predictive prowess holds immense potential for informed decision-making and strategic planning.

In the realm of decision support, computerized information systems known as Decision Support Systems (DSS) play a pivotal role. These systems provide indispensable support for critical decision-making processes within various sectors, including businesses. Furthermore, the integration of Data Mining (DM) techniques within DSS frameworks significantly augments the decision-support capabilities. This synergistic combination extends the possibilities for enhanced decision support, leveraging the wealth of insights that can be derived from comprehensive data analysis. (Zheng et al., 2009b).

By elucidating the intricate dynamics of database and GIS integration and emphasizing the transformative potential of big data analysis, time series analysis, Decision Support Systems, and Data Mining, this section underscores the critical importance of harmonizing data systems to empower more informed and effective decision-making processes across diverse domains.

In the phase of ore reserve estimation, GIS-based technologies play a pivotal role in our pursuit of buried mineral deposits. These technologies offer a versatile toolbox that includes spatial analysis, targeting, 3D data visualization, and data processing. With these tools at their disposal, researchers can effectively pinpoint and evaluate subterranean mineral reservoirs by uncovering critical information about their precise locations, dimensions, and geometries.

As the research progresses, structural conflicts come into focus. In the absence of physical conflicts, a practical approach is chosen, reconfiguring classes by seamlessly blending compatible attributes. However, when operational conflicts emerge, a consensus-building process among local administrators is relied upon. This collaborative effort results in crucial decisions, helping to create classes with shared properties, the establishment of hierarchical class structures, or the specification of transformation functions applied to formats, domains, units, and other attributes.

This comprehensive resolution process ensures the cohesive integration of GIS and database systems, aligning data seamlessly with the diverse requirements of the mining industry. By harnessing the power of GIS-based technologies and systematically addressing integration challenges, the ability to unearth and estimate mineral deposits can be enhanced efficiently and accurately. In this phase the primary goal is to tackle the semantic and mechanical conflicts that often arise during the integration process. Our task is to harmonize the geographic objects from different schemas into a unified global schema.

2.7 Use of GIS in the Underground Mining Cycle

According to Kurwi (2019), the **Table 1** shows examples of lifecycle phases where integrating Database and GIS can be used. The plan involves connecting the information outlined in Table 2, GIS-cycle, with the gallery obtained from the media department, which shows images of the working area and how workers complete the mining process. The gallery will be color-coded to match the joint, and an arrow will be drawn to indicate the direction of the process. This process should be repeated until the terminus is reached.

Table 1: Examples of database and GIS integration

Lifecycle phases	Application
Planning and Design	♦ Site selection ♦ Climatic calculation through integrating project models and MINING data from GIS databases. ♦ Assess and enhance energy-efficiency performance by semantic web technologies. ♦ Interior acoustic design base on an integrated mining-GIS platform
Construction	Managing supply chain in a visualized construction supply chain management system
Operation and Maintenance	♦ Emergency answer and interior navigation ♦ Ability asset organization ♦ Noticing and plotting the information for pipe networks ♦ Flood damage assessment (FDA)
Destruction	Waste approximation, waste sorting and calculation

Table 2: Starting and End Nodes of work.

<i>From</i>	<i>To</i>	<i>Distance (m)</i>
127	130	26
130	132	18
130	129	26
132	134	55
129	125	20
125	124	27
125	128	7

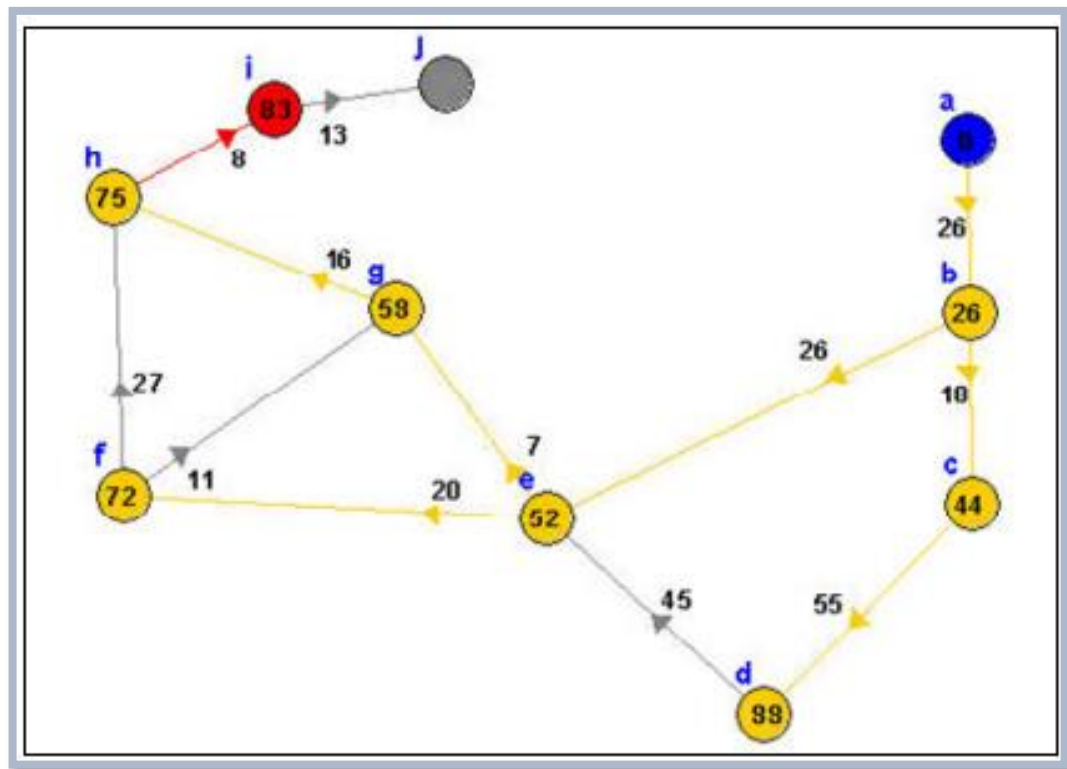


Figure 7: Mining path Kurwi (2019)

Table 2 shows the data provided as the input to the GIS system. authenticated consequence was the same as the image output. Program highlights the shortest path with red color after running the process in **Figure 7: Mining path**, and **Table 3** provides the explanation about the data.

Table 3: Data Explanation

Where	Refers to
UTM	Name of coordinate system
8	Projection type used
Datum Used	Units Used
7	Units Used
15,0	Origin Longitude and Origin Latitude
0	Scale factor used

2.8 Summary

The integration of data within distribution systems represents a substantial undertaking that demands a robust commitment to enhancing GIS systems for mining data management. This research project has led to the development of a GIS-based tool, characterized by its lightweight architecture. This tool has been successfully implemented in five different facilities across North America and Europe, each presenting its unique challenges and specific requirements for proactive decision integration. Originally conceived to specifically address mining excellence issues, this tool has since evolved into a versatile instrument capable of integrating various forms of evidence related to distribution systems, proving its value for broader distribution system management purposes.

The application of GIS in the mining industry offers several key advantages, including its utility in mine planning, process enhancement, and environmental impact assessment. Python, with essential libraries like NumPy, SciPy, and pandas, serves as a crucial toolkit for geometric calculations and scientific computations within this context. Furthermore, this research paper underscores the significance

of GIS in promoting underground mining safety, emphasizing its role in data display and retrieval.

The advantages of GIS dashboards have been explored, highlighting their capacity to efficiently capture, analyze, and visualize geographically referenced information. GIS dashboards offer a consolidated view of maps, applications, and real-time event monitoring, proving invaluable for bolstering geospatial infrastructure. This literature review shows utility of GIS applications in mining data management, underlining its multifaceted utility across various facets of the industry and positioning it as a critical tool for enhancing decision-making processes and safety measures.

3. CHAPTER THREE - MATERIALS

3.1 Introduction

This chapter discusses the materials and methodology employed in the research. It begins with a discussion of the study area, followed by an exploration of the data sources used to develop the GIS system for monitoring the underground mining environment. The chapter also delves into the process of data acquisition and pre-processing.

3.2 Study Area

The Sibanye Stillwater Digital Mining Laboratory (DigiMine) is a state-of-the-art facility dedicated to enhancing the safety and sustainability of mining through digital technologies. It enables a mine's control system to autonomously observe, evaluate, and respond, including moving towards real-time actions. This Mock Mine is located in the Chamber of Mines building at the University of Witwatersrand. The purpose of DigiMine is to provide researchers with the opportunity to conduct tests, research, and development, and seek innovation by transferring surface digital technologies into the underground mining environment. The research at DigiMine involves deep partnerships with commercial, academic, and industry entities.

The Wits DigiMine is a research facility that consists of both a surface control room and an underground mock-up mine. The surface control room houses a central computer that facilitates communication of data with the underground section. The underground part of DigiMine comprises a 70-meter-long tunnel structure adjacent to a stope area. This underground area is equipped with monitoring sensors and

wireless communication capabilities. Notable infrastructure within the tunnel includes a model stope panel, a rescue bay, and a lamp room. The facility was purposefully established for research activities and is equipped with underground mine monitoring systems, supplying the necessary data for the research project. Additionally, there is a weather station installed on the roof of the building, providing meteorological data for a comprehensive understanding of the underground mining environment.



Figure 8: Chamber of Mines building.

The Chamber of Mines building is depicted in **Figure 8: Chamber of Mines Building**. The annotations on the figure highlight two areas of interest for this research:

- a) Mock Mine
- b) Weather Station

Figure 9 shows the view inside of the tunnel that offers an interior perspective of the mock mine. Within this visual representation, key elements are highlighted. The ventilation system, crucial for maintaining air quality and circulation, is positioned on the top left of the view. Meanwhile, the mine blast system, responsible for managing controlled explosions during mining operations, is visually represented in orange on the right side of the figure. This depiction provides a clear visualization of the spatial arrangement of these significant components within the underground environment of the mock mine.



Figure 9: View Inside the Tunnel

3.3 Monitoring Systems

The mock mine is outfitted with a diverse array of monitoring systems, encompassing geo-technical, ventilation, a weather station, and an underground mine blast system. The data generated by these monitoring systems played a crucial role in the execution of this research. Furthermore, to enhance the breadth of information, mine production data was generously provided by Sibanye Stillwater. This additional dataset contributed to the development of the dashboards, offering a comprehensive view of both operational and environmental aspects within the mining environment.

3.3.1 Geo-technical Monitoring System

The geo-technical monitoring system at the mock mine comprises seismographs and ground movement sensors. For this research, data sourced specifically from the ground movement sensors was utilized. These sensors are strategically installed throughout the DigiMine Lab facility, as illustrated in **Figure 10**, capturing comprehensive information on ground movements. This data serves as a valuable resource for the research, contributing to a detailed understanding of the geological and structural dynamics within the mock mine environment. **Figure 10**



Figure 10: Ground Movement Sensor on tunnel ceiling.

Ground Movement sensors deliver precise measurements of ground movement, detecting any changes between the two points where the sensor is installed. The accuracy of data acquired from these sensors is in millimeters, enabling the detection of even small movements in the ground. This capability is crucial for ensuring the safety of mineworkers, as it allows for the identification of ground shifts, prompting timely and appropriate actions to maintain a secure working environment.

The geo-technical monitoring system incorporates strain gauge, strategically installed at various locations, including the stope and tunnel. These meters provide accurate indications of the stress exerted on the structures they are mounted on. Assessing stress on both rocks and support structures is crucial for evaluating the stability of the mine, a significant aspect illustrated in **Figure 11** and **Figure 12**.



Figure 11: Strain gauge installed on the stope support.



Figure 12: Strain gauge installed on the ceiling in mock mine.

The data collected from the geo-technical monitoring system possesses the following key characteristics:

- Spatial Dataset and Geo-Tagging:
 - The sensors in the geo-technical monitoring system are fixed at specific locations, and their positions are well-defined. This characteristic facilitates easy geo-tagging of the data, making it spatially referenced. The known locations enable the integration of the data into a spatial dataset, allowing for precise mapping and analysis.
- Temporal Frequency:
 - Data is recorded at a temporal frequency of 15 minutes. This implies that measurements are taken and recorded every 15 minutes, providing a detailed and frequent temporal resolution. This frequency is essential for capturing

real-time or near-real-time changes in ground movement and rock stress, offering a comprehensive understanding of dynamic geological conditions.

- Data Format:
 - The recorded data is stored in a CSV (Comma-Separated Values) file format. This format is commonly used for tabular data and allows for easy export from the monitoring system. The manual export process suggests a periodic retrieval of data, possibly aligned with specific analysis or reporting intervals.
- Number and Type of Sensors:
 - The geo-technical monitoring system comprises a total of 6 sensors. Among these, 4 sensors are dedicated to ground movement measurement, providing information about shifts in the ground. Additionally, 2 sensors are rock stress sensors, which focus on measuring stress levels within the rocks and support structures. This combination of sensors ensures a comprehensive data set, capturing various aspects of the geological and structural dynamics within the monitored environment.

The geo-technical monitoring system generates spatially referenced data with a high temporal frequency, recorded in CSV format through manual export. The inclusion of both ground movement and rock stress sensors enhances the system's capability to provide a holistic understanding of the monitored area.

The limitations of the geo-technical mine monitoring system in terms of data can be summarized:

- Limited Direct Access to Sensor Data:

- One limitation is the lack of direct access to sensor data. Instead, data retrieval depends on the use of software provided by the system manufacturer. This indirect access may introduce delays and dependencies on the manufacturer's software, potentially affecting the efficiency of data retrieval and analysis.
- Temporal Resolution:
 - The data collected from the sensors has a temporal resolution of 15 minutes. While this provides a reasonably detailed snapshot of ground conditions, it falls short of the ideal scenario of real-time streaming data. This limitation may affect the system's ability to capture rapid changes in geological conditions with high precision.
- Manual Export Process:
 - Another limitation is the manual export process required to download the data. This manual step introduces a delay between the recording of data and its availability on the GIS dashboard. The time-consuming nature of the export process adds to the latency in data presentation, potentially affecting the system's responsiveness to real-time or near-real-time changes in the monitored environment.

The geo-technical mine monitoring system faces challenges related to indirect data access through manufacturer-provided software, a temporal resolution of 15 minutes instead of real-time streaming, and a manual export process that introduces delays in making the data available for visualization on the GIS dashboard. These

limitations should be considered when assessing the system's capabilities and responsiveness in capturing dynamic geological conditions.

3.3.2 Ventilation System

Underground mines, due to their confined nature, require effective ventilation to prevent the buildup of dangerous gases. Ventilation maintains a habitable environment for mine workers and preventing the concentration of harmful gases. Gas concentration sensors are essential in detecting and alarming mine workers in the event of gas leaks or the buildup of lethal gases such as methane and carbon monoxide. Monitoring these gas concentrations is crucial, as exceeding safe levels can have fatal consequences for the safety and well-being of mine workers.

The characteristics of the data collected from Gas concentration sensors are summarized:

- **Spatial Dataset and Geo-Tagging:**
 - The sensors are stationary and fixed at specific locations, allowing for easy geo-tagging. This characteristic transforms the data into a spatial dataset, as the precise location of each sensor is known. This spatial reference is valuable for mapping and analyzing gas concentrations across different areas.
- **Gas Concentration Values:**
 - The data captured by these sensors includes values representing concentrations of harmful gases. This information is critical for monitoring and assessing the safety of the underground environment, as it provides insights into potential risks associated with gas accumulation.

- Temporal Frequency:
 - Data is recorded at a temporal frequency of 15 minutes. The sensors capture gas concentration values at regular intervals, providing a detailed temporal resolution. This frequency enables the monitoring system to detect changes in gas concentrations over time and respond to emerging safety concerns.
- Data Format:
 - The recorded data is stored in a CSV (Comma-Separated Values) file format. This format facilitates easy export from the monitoring system. However, the manual export process may introduce some delay between data recording and its availability for further analysis.

The data collected from Gas concentration sensors is spatially tagged, includes values of harmful gas concentrations, has a temporal resolution of 15 minutes, and is exported in CSV format through a manual process. These characteristics contribute to a comprehensive dataset that aids in understanding and managing gas-related risks in the underground mining environment.

The limitations of Gas concentration sensors in terms of data handling can be summarized:

- Indirect Sensor Data Access:
 - One limitation is the inability to directly access data from the sensors. Instead, data retrieval relies on using the software provided by the system manufacturer. This indirect access introduces potential dependencies and may affect the efficiency of data extraction and analysis.

- Temporal Resolution:
 - The temporal resolution of the collected data is set at 15 minutes. While this frequency provides periodic snapshots of gas concentrations, it falls short of the ideal scenario of having a continuous stream of real-time data directly from the sensors. This limitation may affect the system's ability to promptly respond to rapid changes in gas levels.
- Manual Export Process:
 - Data export is a manual process that takes time to download the data. The manual nature of this export process introduces a delay in making the data available for visualization on the GIS dashboard. This delay can impact the system's responsiveness, especially in situations where real-time or near-real-time monitoring is crucial.

These limitations highlight considerations related to data accessibility, temporal resolution, and export efficiency when evaluating the performance and responsiveness of Gas concentration sensors, particularly in the context of timely decision-making and visualization on the GIS dashboard.

3.3.3 Blast System

The Blast system installed in the mine serves the crucial purpose of simulating blasts within the tunnel. The system, present at DigiMine, features 40 detonators and BlastWeb II underground blasting system. Integrating blast data with information from other monitoring systems is deemed valuable for identifying anomalies that may arise due to the blast itself while ensuring the overall stability of the mine.

Blasts are acknowledged as a critical component of underground mining operations, and the data collected from detonators becomes instrumental for mine managers. The Blast system at the mock mine is characterized as sophisticated, offering blast technicians the capability to precisely program the pattern and timings of each detonator. The system allows for millisecond precision in setting the time differences between detonators, enhancing control and safety measures during the blasting process.

The characteristics of the data collected from the Blast system are summarized:

- Detonator Information:
 - Data collected from the Blast system includes details about the number of detonators connected and the number of detonators blasted during each operation. This information provides insights into the scale and magnitude of the blasts conducted within the mine.
- Export Format and Filtering:
 - The collected data is exported as reports, and it can be filtered based on specific criteria such as each day or each individual blast. The ability to filter the data using the blast web software enhances the flexibility and usability of the information for detailed analysis and reporting.
- Blast Technician and Supervisor Information:
 - The data contains information about the blast technician and supervisor who authorized each blast. This additional contextual information is valuable for accountability and traceability, allowing for a comprehensive understanding of the individuals involved in the blasting operations.

The data collected from the Blast system includes details about detonators, exportable reports with filtering options, and information about the blast technician and supervisor. These characteristics contribute to a comprehensive dataset that facilitates detailed analysis and management of blasting activities within the underground mine.

The limitations of the Blast system in terms of data handling can be:

- **Limited Detonator Information in Reports:**
 - The reports generated by the Blast system provide information only on the total number of detonators that blasted during each operation. However, they do not specify which specific detonators were defective or experienced issues. This limitation might hinder a detailed analysis of individual detonator performance.
- **Manual Export Process:**
 - The export process for the data collected by the Blast system is manual and time-consuming. This manual step introduces delays in downloading the data, increasing the time between the recording of data and its availability on the GIS dashboard. This delay may impact the system's responsiveness, particularly in scenarios where real-time or near-real-time monitoring is crucial.

These limitations highlight considerations related to the specificity of detonator information and the efficiency of the export process when evaluating the performance and responsiveness of the Blast system, especially in the context of timely decision-making and visualization on the GIS dashboard.

3.3.4 Weather Station

A weather station, located on the surface, plays a crucial role in collecting essential environmental data such as rainfall, temperature, air pressure, and wind. This information is vital for managing underground ventilation settings. The geothermal gradient, a phenomenon where temperature increases with depth, is significant in mining operations. In the Johannesburg area, for instance, the heat increases by approximately 1 degree Celsius for every 100 meters vertically down (Dhansay et al., 2017). Understanding the surface temperature is essential for establishing how much the underground areas must be cooled down. This data from the weather station informs ventilation strategies, allowing for effective temperature control and creating a safer and more comfortable working environment for individuals within the mine.

A weather station is installed on the roof of the Chamber of Mines building for the DigiMine lab. The installed weather station collects data about air temperature, humidity, and rainfall. For this research, only the datasets related to air temperature and humidity from the weather station have been used in the integrated system.

The characteristics of the data collected from the weather station are summarized:

- **Spatial Dataset and Geo-Tagging:**
 - The weather station is fixed at a specific location, and its precise location is known. This characteristic allows for easy geo-tagging, making the data a spatial dataset. Spatial information enhances the ability to analyze and visualize weather patterns in specific geographical areas.
- **Temporal Frequency:**

- Data is recorded at a temporal frequency of 15 minutes. The weather station captures air temperature and relative humidity values at regular 15-minute intervals. This temporal resolution provides detailed insights into how these weather parameters change over time.
- Data Format:
 - The recorded data is stored in a CSV (Comma-Separated Values) file format. This format facilitates easy export from the weather station system. However, the export process is manual, requiring human intervention to download the data.
- Included Parameters:
 - The data includes two main parameters: air temperature, measured in degrees Celsius, and relative humidity. These parameters offer key insights into the atmospheric conditions at the specific location of the weather station.

The data collected from the weather station is spatially tagged, has a temporal resolution of 15 minutes, is exported in CSV format through a manual process, and includes information on air temperature and relative humidity. These characteristics contribute to a comprehensive dataset for analyzing local weather conditions.

The limitations of the weather station dataset in terms of data handling can be summarized:

- Indirect Sensor Data Access:

- The data cannot be accessed directly from the sensors. Instead, it needs to be exported using the software provided by the system manufacturer. This indirect access introduces potential dependencies and may impact the efficiency of data extraction and analysis.
- Temporal Resolution:
 - The temporal resolution of the data is set at 15 minutes. While this frequency provides periodic snapshots of air temperature and humidity, it falls short of the ideal scenario of having a continuous stream of real-time data directly from the sensors. This limitation may affect the system's ability to promptly respond to rapid changes in weather conditions.
- Manual Export Process:
 - The export process for the data is manual and takes time to download. This manual step introduces delays in making the data available for visualization on the GIS dashboard. The delay may impact the system's responsiveness, especially in situations where real-time or near-real-time monitoring is crucial.

These limitations highlight considerations related to direct data access, temporal resolution, and export efficiency when evaluating the performance and responsiveness of the weather station dataset, particularly in the context of timely decision-making and visualization on the GIS dashboard.

3.3.5 Mine Production Data

Underground mines represent substantial investments with significant operational costs. The insights derived from mine production data are invaluable for mine

managers. Tasked with the responsibility to optimize operational efficiency, mine managers rely on these insights to make informed decisions and maximize the utilization of resources within the mine.

The provision of mine production data by Sibanye Stillwater for inclusion in the dashboard signifies a collaborative effort between Sibanye Stillwater and the research project. This data is expected to be a crucial component of the dashboard, offering insights into various aspects of mine production such as equipment utilization and plant efficiency. The collaboration underscores the importance of industry partnerships and the willingness of mining companies to contribute valuable data to enhance research and decision-making processes.

The mine production data provided by Sibanye Stillwater for inclusion in the dashboard has these characteristics:

- Information Included:
 - The data contains information about Equipment Utilization and Plant Efficiency. These metrics are crucial for assessing the performance and efficiency of equipment and plant operations within the mine.
- Temporal Resolution:
 - Data is collected on a daily basis. This daily frequency allows for a detailed analysis of trends and variations in equipment utilization and plant efficiency over time.
- Data Format:

The data is provided in CSV (Comma-Separated Values) format. This format is widely used and facilitates easy handling, integration, and analysis of the data within the dashboard.

These characteristics highlight the key aspects of the mine production data, emphasizing its focus on essential metrics, the frequency of collection, and the accessible format for integration into the dashboard.

The mine production data, despite being valuable, has certain limitations:

- Manual Data Collection:
 - The data collection process is manual, which implies that there is a considerable amount of time between the actual occurrence of events in the mine production process and the availability of that data on the dashboard. This delay may affect the real-time nature of decision-making.
- Access Restrictions:
 - Mine production data is considered sensitive business information. Consequently, access to this data is restricted and limited to specific management personnel. This limitation is in place to ensure the confidentiality and security of critical business insights.

These limitations highlight challenges related to the timeliness of data availability and the need for careful management of sensitive information in the mining industry.

3.4 Data Summary

Table 4 summarizes the datasets collected for this research, outlining the key attributes related to each dataset:

Table 4: Summary of Datasets

<i>Data</i>	<i>Frequen cy</i>	<i>Locati on</i>	<i>Attributes</i>	<i>No. of Sensors</i>	<i>Features</i>
Equipment Utilization	1 Day	–	Shift Hours, Utilization, Availability, Efficiency	N/A	N/A
Plant Efficiency	1 Day	–	Equipment, Value	N/A	N/A
Ground Movement	2-5 Minutes	Mock Mine, PG Office	Movement	4	Range: Can measure displacements from millimeters to several meters Accuracy/Precision: High accuracy: $\pm 0.1\text{mm}$
Detonations	1 Day	Mock Mine	Dets Blasted Dets Connected	N/A	N/A
Gas Concentration	5 Minutes	Mock Mine	Gas Concentrations	4	Methane Range: 0 – 2 % lel CO Range: 0 – 50 ppm
Stope Rock Stress	15 Minutes	Mock Mine, Stope	Pressure	2	Range: 0-100 MPa (0-14,500 psi) Accuracy/Precision: $\pm 0.2\%$ - 1% of full scale depending on model and manufacturer.
Weather	15 Minutes	Roof	Air Temperature, Relative Humidity	1	Temperature Range: -40 - 80 °C Precision: ± 0.2 - $\pm 1^\circ\text{C}$ Humidity Range: 0 – 100 % Precision: ± 2 - ± 5 %

This summary table summarizes the various datasets, including the frequency of data collection, locations where the data was gathered, attributes captured in each dataset, and the number of sensors associated with specific datasets.

3.5 Summary

Chapter 3 outlines the materials and methodology used in the research, starting with an overview of the study area, the Sibanye Stillwater Digital Mining Laboratory (DigiMine). The chapter covers data sources, acquisition, and pre-processing methods.

The study area (DigiMine), located at the University of Witwatersrand, is a cutting-edge facility focusing on digital technologies for mining safety and sustainability. The research involves partnerships with commercial, academic, and industry entities. The facility includes a surface control room and an underground mock-up mine, providing valuable data for research.

The mock mine features various monitoring systems, including geo-technical, ventilation, a weather station, an underground mine blast system, and mine production data from Sibanye Stillwater. Each monitoring system has unique characteristics and limitations.

The geo-technical monitoring system contributes spatially tagged data with a temporal frequency of 15 minutes, recorded in CSV format manually. It comprises 6 sensors—4 ground movement and 2 rock stress sensors.

Ventilation, crucial for safety, is monitored using gas concentration sensors. Data includes spatially tagged values of harmful gas concentrations, recorded every 15 minutes in CSV format through manual export.

The blast system with 40 detonators allows precise programming. Data includes detonator details, exportable reports, and blast technician/supervisor information.

Surface weather data, focusing on air temperature and humidity, aids in ventilation strategies. Data includes spatially tagged information recorded every 15 minutes in CSV format through manual export.

Sibanye Stillwater provided mine production data focusing on equipment utilization and plant efficiency, collected daily in CSV format.

Chapter 3 provides a comprehensive understanding of the research materials, emphasizing the significance and limitations of each data set. The detailed overview sets the stage for the subsequent methodology and analysis chapters. In following Chapter 4 which will delve into the development of a GIS-based underground mine monitoring system, exploring its features and functionalities. The focus will be on providing a comprehensive understanding of the system's capabilities in integrating and analyzing diverse datasets obtained from monitoring systems within the underground mining environment. This chapter will likely detail the GIS system's architecture, user interface, and how it harnesses the collected data to facilitate informed decision-making and real-time monitoring of critical aspects such as ground movement, ventilation, blast events, and weather conditions. By elucidating the system's features and functionalities, the chapter aims to demonstrate its effectiveness in enhancing safety, sustainability, and operational efficiency in underground mining activities.

4. CHAPTER FOUR - INTEGRATED UNDERGROUND MINE MONITORING SYSTEM

4.1 Introduction

In this chapter the GIS based Underground Mine Monitoring system is discussed. Data flow and Data processing are also discussed. This chapter includes a detailed methodological flow chart to create an Integrated GIS based mine monitoring system.

4.2 Conceptualization of Monitoring System

The concept of this research was to develop a monitoring system where underground mine monitoring data can be visualized online. In this monitoring system the data update process was developed to be automated. This monitoring system was developed to be used by mine management. To make it accessible it was developed so that minimum technical skills are required to keep data updated. This system also has the capability to include further monitoring systems and sensor data sets in it without need for further development.

4.3 Dynamic and Scalable System

A dynamic and scalable monitoring system is a system that can efficiently and effectively track and analyze data in near real-time, adapt to changes in the system, and expand its capacity to handle larger amounts of data as needed. It is designed to be flexible and responsive to changes in the environment or the system being monitored, while also being able to handle large amounts of data without becoming overwhelmed or experiencing delays.

The system design in this research was designed to be flexible. Data from new sensors can be easily accommodated to the system by updating the configuration file, with no need for new development work. The system is also flexible, allowing users to edit the dashboards online and update the visualization to fulfill their specific needs.

4.4 Detailed Methodological Flow Chart

To create an Integrated GIS based mine monitoring system five main components were developed.

1. Data Collection
2. Data Storage
3. Analysis
4. Data Visualization
5. Warning System

The detailed methodological flow chart of whole system is shown in **Figure 13**.

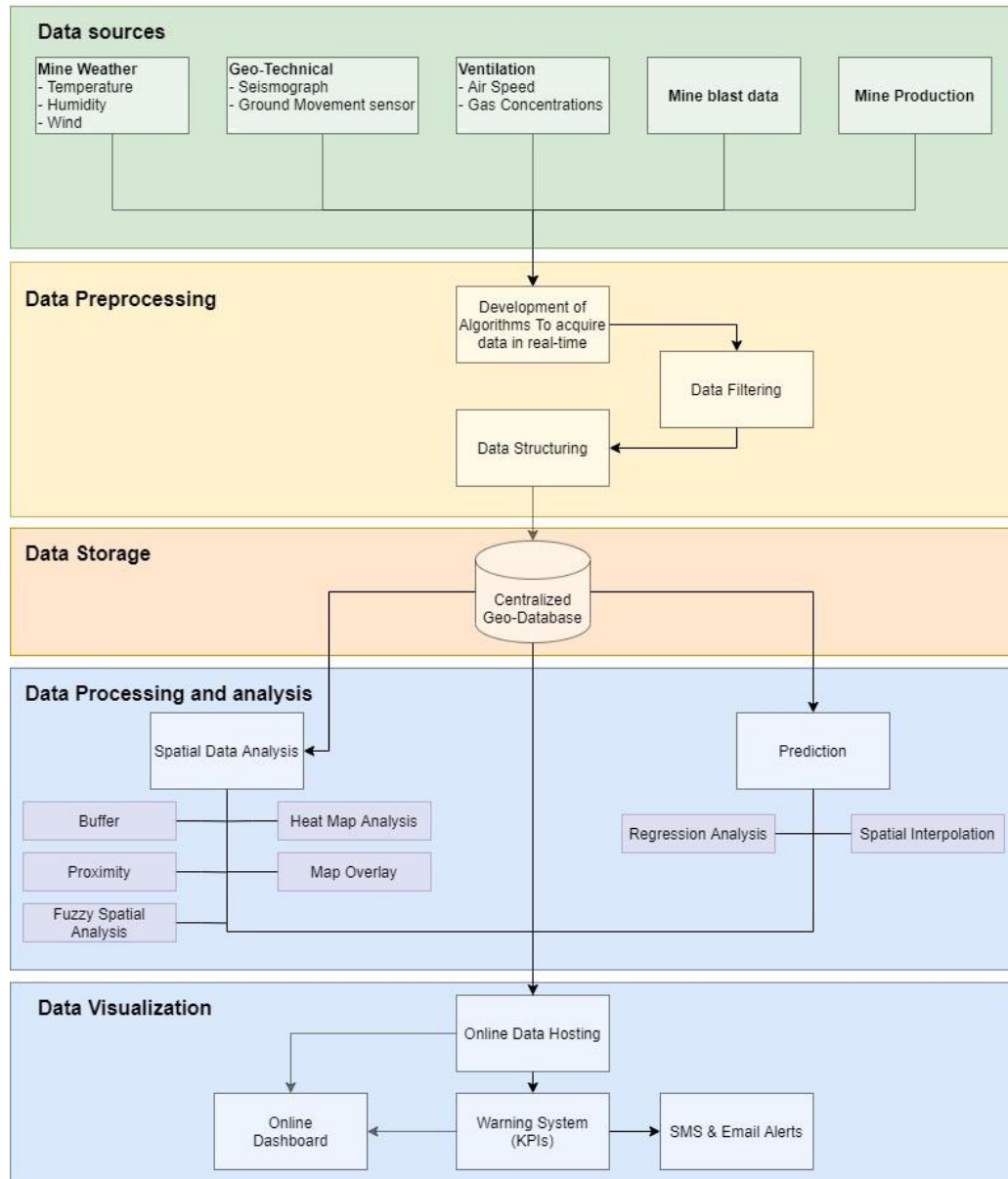


Figure 13: Detailed Methodological Flow Chart

Above figure shows the data flow from sensors to database to processing to visualization:

- Sensor data collection: Data was collected from various sensors, which could include temperature sensors, humidity sensors, air quality sensors, and others.

- Data pre-processing: The raw sensor data was pre-processed to remove any irrelevant data, convert the data into a standard format, and remove any errors or inconsistencies in the data.
- Data storage: The pre-processed data was then stored in a database for future use.
- Data processing: The stored data was then processed to extract useful information from it. This includes proximity analysis, data interpolation and data prediction using statistical algorithms.
- Data visualization: The processed data was then visualized in a format that is easy to understand and interpret. This includes graphs, charts, and maps that help to display the data in a meaningful way.
- User interaction: The visualization was then made available to the end user, who can interact with it to explore the data in more detail or to adjust the visualization settings.

Overall, this flowchart shows how data flows from sensors through pre-processing, storage, processing, and visualization before being made available to end-users. The process involves a combination of hardware and software components, including sensors, databases, processing algorithms, and visualization tools, all working together to create a complete data management and analysis system as shown in **Figure 14.**

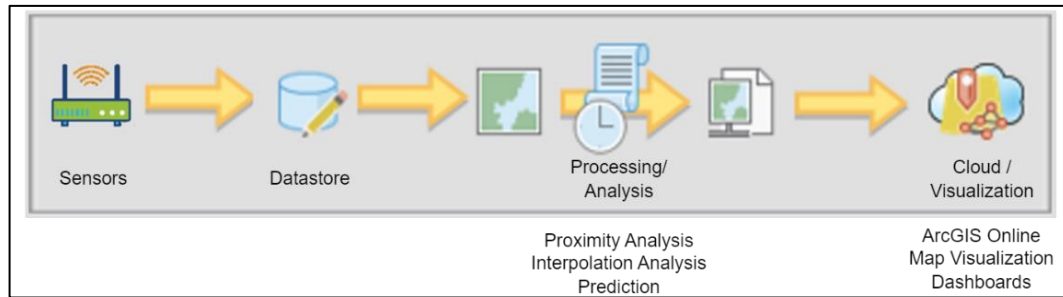


Figure 14: Data Flow

4.5 Data Collection

Data was collected regarding the underground mining environment and geotechnical parameters. The various parameters of underground mining environment such as gas concentrations, temperature, humidity, wind speed and ventilation as well as geotechnical parameters such as seismic sensors and blast data were collected. These parameters were measured using systems deployed by several companies at mine. To collect the data python scripts were developed. Data was collected from the deployed system database and where direct access on the database was not provided so the csv exported files were used to load data to the system.

Python is a powerful scripting language. It is one of the top languages used for GIS development. Python has been in development for more than 2 decades. It is widely used for automation scripts and data analytics. Python community has developed various open-source modules for scientific community that were used in this research including NumPy that is used for numerical computation, SciPy which is an enhanced package for Scientific computations, Pandas used for analysis and manipulation of data structures. In this research python was used to automate data collection, data preprocessing and development of warning system.

Data collection was the first step for data integration and management. As data was collected from various sources the temporal frequency, measurement units, collection method and number of attributes also vary. To handle data a framework was developed using python. A configuration file was used to guide the system to load data from the source, perform the preprocessing and then upload it to the database.

The Configuration file contains information about the data source. Using the configuration file new data source can be simply added just by adding the information about the source i.e., what is the type of data source e.g., a CSV file, a PostgreSQL database, a SQL database or Excel spread sheet. How to access the data source if it is a file then the location of file otherwise if it is a database then the host address, port, username, and password. Then preprocessing function names can be named here that will be performed to rectify / restructure the data. Lastly name of the table where this data will be added to the central database.

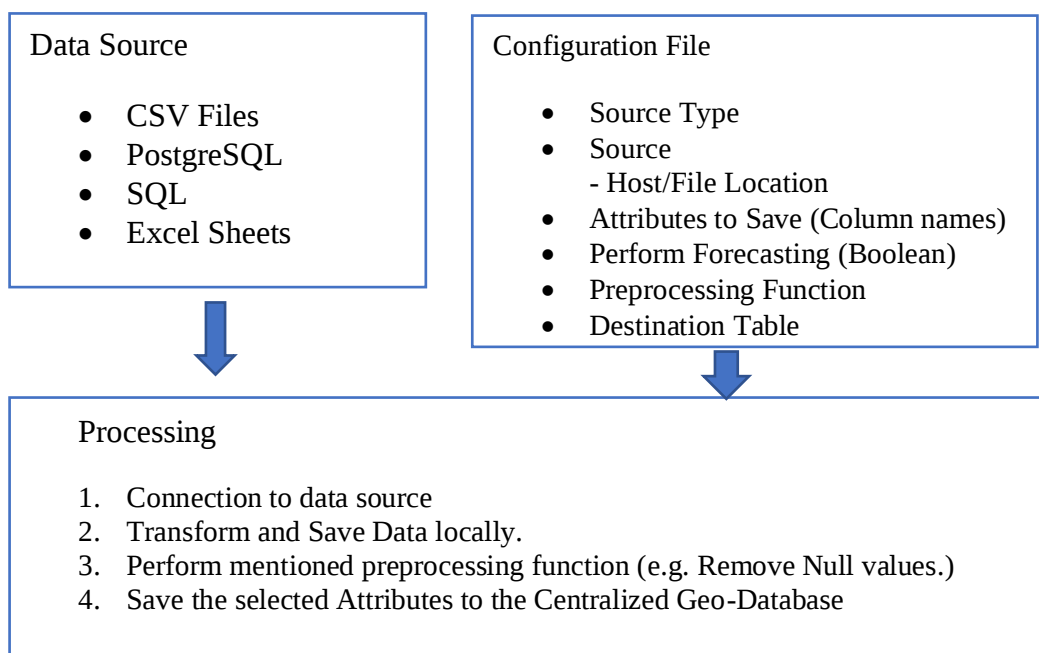


Figure 15: Process Flow

4.6 Centralized Geo-Database

To store the data a centralized PostgreSQL database was used. Before the data was stored on the database was pre-processed. Python scripts were developed to pre-process the data. Data is restructured and cleaned to store on the database. PostGIS extension was installed on PostgreSQL to accommodate location-based data.

PostgreSQL is a very robust opensource database. It has been an open-source project in development for more than 30 years now. It is an object relational database system (ORDBMS) and uses standard SQL as its databased interface language. Several types of indexes including BTree, Hash, Generalized Inverted Indexes (GIN) and Generalized Search Tree (GST) are supported by PostgreSQL. BTree is the default indexing type. It can increase performance for equality and range queries moreover it can be applied for any datatype.

To enable spatial capabilities of the database, a special extension was used called PostGIS. Several geo-functions and geographical objects are supported with the help of this extension. Points, LineStrings, Polygons, MultiPoints, MultiLineStrings, MultiPolygons and Geometry Collections can be created using Post GIS extension. The Database scheme for the study is shown in **Figure 16**.

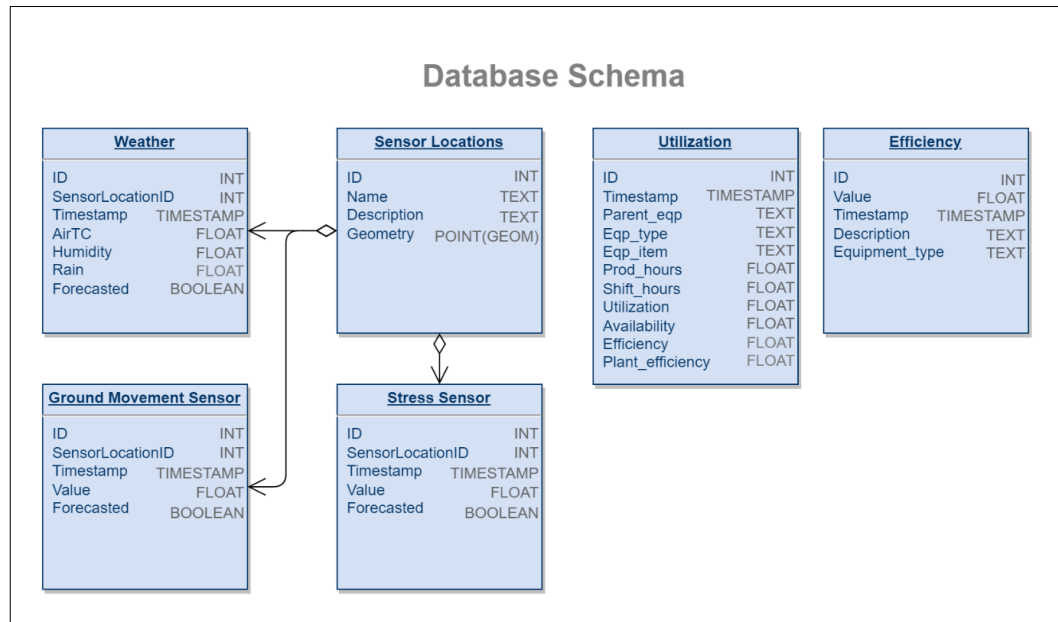


Figure 16: Database Schema

4.7 Analysis

Analysis was performed on the collected data to extract valuable information. Regression analysis was performed on the data to predict future values on the tabular sensors data. GIS analyses were performed to create maps from the geo-tagged sensor data. Interpolation analysis was performed to get estimated values where there is missing information. Overlay Maps were created so a parameter can be visualized in context of other parameters. ArcGIS Pro was used to perform this analysis.

ArcGIS is a GIS platform developed by ESRI. ArcGIS is the most used commercial software used in GIS field. It provided tools for all kinds of location-based analysis. Contextual tools are provided by ArcGIS to visualize and analyze that provides greater insights. It provides analytics methods and spatial algorithms which enables the users to connect data and leverage power of data science and spatial analytics.

ArcGIS pro is a desktop application provided by ArcGIS platform. It has unparalleled data analytics and Spatial processing capabilities. It was used to create the map locally and perform spatial analysis on the data. ArcGIS pro also comes with the ArcPy module for python scripting. ArcPy was used to upload data on ArcGIS online. The scripting capability allows us to perform periodic updates to the data on ArcGIS online platform.

Spatial interpolation was performed on the data to estimate unknown values of a variable at unsampled locations within a region based on the values of the variable at sampled locations. In simpler terms, it is a method to estimate values of factors like temperature or humidity at points where actual measurements are not available, using the values from points where sensors have been installed and measurements have been taken.

K-means interpolation was used in this research, it is the spatial interpolation technique that uses the mean of the k nearest measured values to estimate the value at an unsampled location. The basic formula for k-means interpolation is:

$$Z(u) = (1/k) * \sum Z_i$$

where $Z(u)$ is the estimated value at the unsampled location u , Z_i is the measured value at each of the k nearest sampled locations, and k is the number of nearest neighbors used in the interpolation.

Prediction was made using ARIMA (Autoregressive Integrated Moving Average) which is a popular time series analysis and forecasting method that models the time series data based on its past behavior. It is a statistical model that can make

predictions about future values of a time series based on its historical patterns and trends.

ARIMA models have three main components:

- Autoregression (AR) - This component models the relationship between a variable and its own past values. It assumes that the value of the variable at any given time depends on its values at previous times.
- Moving Average (MA) - This component models the relationship between a variable and the error term, which is the difference between the actual value and the predicted value. It assumes that the error term at any given time depends on its values at previous times.
- Integration (I) - This component models the changes in the variable over time, which may be due to external factors or other influences not captured by the autoregressive and moving average components.

The usefulness of ARIMA for prediction lies in its ability to capture the underlying patterns and trends in the data and make accurate forecasts based on those patterns. By analyzing past data and identifying trends and patterns, ARIMA can help predict future values of the time series, which can be useful in a variety of applications such as finance, economics, and weather forecasting.

ARIMA is useful where the data is non-stationary, meaning that its statistical properties change over time. By incorporating the integration component, ARIMA can model and remove the trend and other non-stationary components, making it easier to make predictions based on the remaining stationary time series data.

ARIMA was used in this research to predict data for Temperature, humidity and movement sensors.

4.8 Visualization

ArcGIS Online was selected to visualize the data, it is a web-based platform for mapping and spatial analysis that provides a wide range of tools for data visualization. These tools allow users to create dynamic and interactive maps, charts, graphs, and other visualizations that can help them explore and communicate spatial data more effectively.

One of the key features of visualization in ArcGIS Online is the ability to create maps that combine various types of data. Users can easily add layers to their maps and customize them with different styles, colors, and symbols to highlight specific features or trends in the data. Pop up/Info tool in the maps allow users to view the details of a data point in the map.

In addition to maps, ArcGIS Online also provides tools for creating other types of visualizations, such as charts, graphs, and dashboards. These visualizations were created using data from maps and centralized data and were customized to display data in a variety of formats, including bar charts, line charts, and gauges.

Overall, visualization in ArcGIS Online is a powerful tool for exploring, analyzing, and communicating spatial data. By using the various visualization tools available on the platform, users can create dynamic and interactive visualizations that can help them gain new insights into their data and communicate their findings more effectively to others.

ArcGIS Online allows users to add multiple layers to their maps and customize them with various styles, colors, and symbols. This can be useful for visualizing complex datasets and highlighting specific features or trends in the data.

Charts and graphs: ArcGIS Online provides tools for creating a variety of charts and graphs, including pie charts, bar charts, scatterplots, and more. These visualizations can display data in a more concise and accessible way and can be customized to fit specific needs. Tabular Data can be visualized as tables or used as source data for charts and graphs.

4.9 Warning System

A warning system was developed that sends warning emails. if the value in a database exceeds a threshold can work in the following way:

1. Data being added to the database is monitored continuously to check if the value of a particular KPI exceeds a pre-set threshold.
2. If the value in the column exceeds the threshold, the system triggers an alert.
3. The system then sends an email to a pre-defined list of recipients using the Simple Mail Transfer Protocol (SMTP).
4. The email contains a warning message that includes details about the threshold exceeded, the value that triggered the alert, and any other relevant information.
5. The recipients can then take action based on the information in the email, such as investigating the cause of the threshold exceedance or taking steps to address the issue.

Warning emails were sent via SMTP which stands for Simple Mail Transfer Protocol. It is a protocol used to send and receive email messages over the internet. When an email is sent, the email client (such as Gmail or Outlook) uses SMTP to send the message to the recipient's email server. SMTP works by breaking down the email message into smaller parts called "packets" and sending them to the recipient's email server. These packets include the sender's email address, the recipient's email address, the message content, and other information needed to deliver the message.

SMTP uses a series of commands and responses between the sender's email client and the recipient's email server to transfer the email message. This process includes authentication (to verify that the sender is authorized to send email), message formatting, and message delivery. Overall, SMTP is a protocol that enables the transmission of email messages between email clients and email servers over the internet. It breaks down the email message into smaller parts and uses a series of commands and responses to transfer the message from the sender to the recipient.

The KPI thresholds are set using the configuration file of warning system. It contains the SMTP connection credentials and the ranges for KPI so that whenever the KPIs are out of the threshold warning emails can be generated. Warning system is developed with the python scripts and check the data whenever new data is added or existing data is updated making it quick to generate alerts.

4.9.1 Climate KPI

Air temperature, humidity and air speed have considerable effect on the health and comfortability of the under miners. The combination of these three factors is used to determine the climate KPI as Higher temperatures can be tolerated if the humidity

is low and there is adequate amount of air flow. In this case the natural cooling system of the human body can keep the body temperature within comfortable range.

4.9.2 Ground Movement

Ground movement is the other KPI used to identify the risk factor in underground environment if the ground movement is above a certain value, then the mine is considered a dangerous place and can be evacuated immediately until it is declared safe by the officials after thorough inspection.

4.9.3 Gas Concentration

Underground mines can release dangerous gases trapped in rock material. These gases are detected by the installed gas concentration sensors. The area needs to be evacuated if there is dangerous concentration of a harmful gas. Gas concentration is another KPI used to trigger warnings for the mine officials.

4.10 Summary

This chapter outlines the research design, data collection techniques, and data analysis methods used in the study. The research design is described, including the data collection, data processing and data visualization procedure. The data analysis methods are also explained.

5. CHAPTER FIVE - RESULTS AND DISCUSSION

5.1 Introduction

This section intensively explores the functionality of the Geographic Information System (GIS) framework, efficiently designed to coordinate, and manage the diverse data streams generated in mining operations. It commences with the establishment of a centralized geodatabase, serving as the authoritative repository for data collected from strategically positioned sensors across the surveyed area. Enhanced by sophisticated data visualization techniques, the intuitive dashboards translate raw data into engaging narratives, vividly depicting temperature fluctuations, ground movement tremors, and pressure variations, each pixel rich with operational insights.

However, the GIS framework goes beyond visualization, encompassing a proactive alerting mechanism – continuously monitoring data against predefined thresholds. If a parameter breach occurs, expedited email notifications are dispatched to designated personnel, precisely identifying the variable in breach. Robust spatial data storage and management are ensured through platforms like PostGIS or SpatialLite, while frameworks such as Dash or Plotly facilitate interactive data visualization within the intuitive dashboards.

The advanced notification system is powered by real-time data monitoring tools, complemented by email notification services. Through seamless integration of these components, the GIS framework surpasses conventional data management, evolving into a comprehensive ecosystem for mining intelligence – providing real-

time insights and proactive alerting mechanisms to facilitate informed decision-making. Ultimately, this ecosystem serves as a stronghold safeguarding operational efficiency and safety within the mining environment.

5.2 Centralized Geodatabase

A scrupulously designed centralized geospatial data repository has been efficiently devised, meticulously crafted to accommodate diverse data streams sourced from multiple sensors, encompassing temperature gauges, ground displacement sensors, and pressure monitoring devices. These data streams are harnessed in the form of CSV exports, meticulously curated from sensors deployed within the subterranean depths of the mining operation. The primary objective behind developing this database infrastructure is to catalyze a paradigm shift towards enhanced efficiency and precision in data management and analysis, thereby fostering optimization within the mining environment.

In the systematic development phase of the centralized geo database, a comprehensive inventory of each data source was rigorously compiled, accompanied by a detailed comprehension of their respective formats and structures. This meticulous groundwork laid the foundation for the subsequent design of a robust database schema, diligently tailored to accommodate a myriad of data types, ensuring seamless integration and structured organization of data tables.

Subsequent to the meticulous blueprinting phase, a suite of cautiously crafted scripts was engineered to automate the intricate process of importing CSV files into the database environment. These scripts, heedfully designed to uphold data integrity standards, seamlessly handle data cleaning procedures and execute any requisite data transformations. As a result, the centralized geodatabase emerges as a stalwart

repository, adeptly storing data from diverse sources in a structured and readily accessible format, ready to be harnessed by authorized personnel through custom-designed dashboards.

One of the pivotal advantages conferred by the centralized geo database is its capacity to revolutionize data management and analysis practices. By standardizing data formats and establishing a uniform data storage framework, the centralized repository streamlines the integration and analysis of disparate datasets, fostering a holistic understanding of mining operations. This streamlined approach enhances the efficiency of data manipulation tasks and expedites the generation of actionable insights, thereby bolstering operational decision-making processes within the mining domain.

Furthermore, the centralized geo database facilitates a comprehensive historical record of mining activities, enabling retrospective analysis and trend identification. Through longitudinal examination of historical data, operators gain invaluable insights into the evolution of mining conditions, enabling proactive measures to be implemented to mitigate risks and optimize operational efficiency.

Moreover, the utilization of advanced data analytics techniques within the centralized geo database offers the potential for predictive modelling and forecasting. By leveraging historical data patterns, predictive algorithms can anticipate future trends and potential hazards, empowering mining operators to preemptively address challenges and optimize resource allocation.

In summary, the development and implementation of a centralized geospatial data repository represent a significant milestone in the evolution of mining operations.

Through conscientious planning, design, and execution, this repository serves as a cornerstone for enhanced data-driven decision-making, ultimately contributing to the safety, efficiency, and sustainability of mining endeavours. The resultant Database can be viewed in the **Figure 17**:

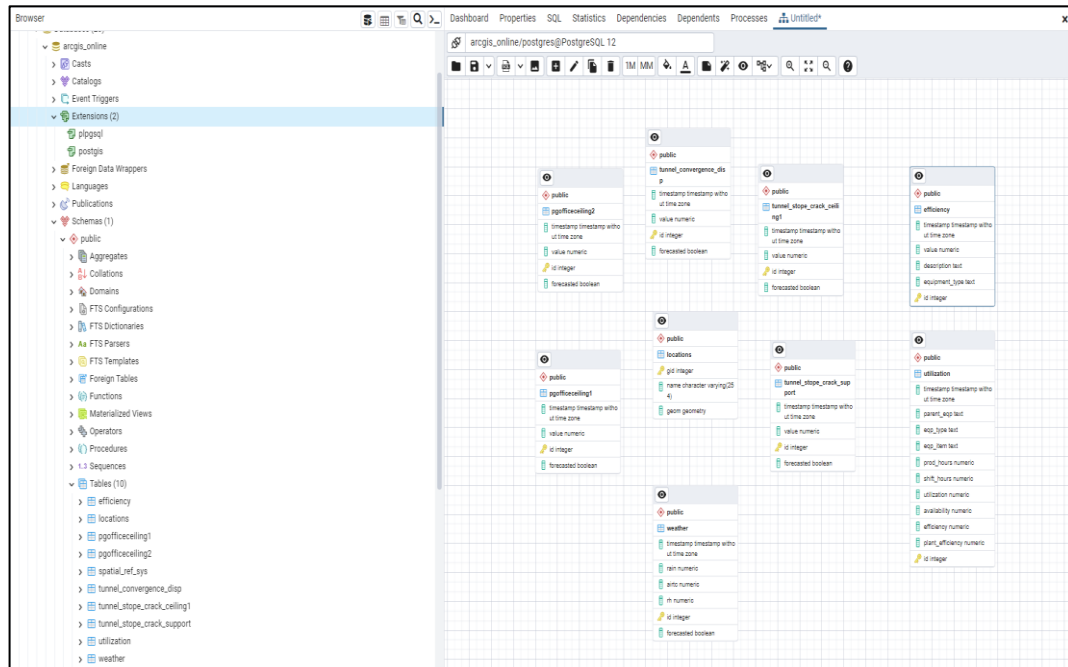


Figure 17: Centralized Geo-Database viewed in PgAdmin.

5.3 Dashboards

The intricate and inherently hazardous nature of subterranean mining operations necessitates a continuous and meticulous monitoring regime to prioritize the safety of both personnel and equipment. This perpetual vigilance relies extensively on the acquisition and analysis of diverse sensor data, encompassing parameters such as temperature, ground displacement, and pressure, meticulously gathered from strategically positioned sensors throughout the mining environment. This data, constituting the core of operational oversight, is seamlessly channeled into a

centralized database, perpetually refreshed to serve as the singular repository of authoritative operational intelligence.

Leveraging this reservoir of data, bespoke web-based dashboards engineered within the ArcGIS Online framework unlock the potential for comprehensive data visualization. These interactive interfaces, meticulously tailored to fulfill specific operational requirements, serve as conveyors through which raw sensor data is transformed into easily interpretable streams of actionable information. Three distinct iterations of these dashboards have been developed, each catering to diverse operational imperatives, thereby offering multifaceted perspectives on the subterranean landscape.

One such dashboard provides a real-time portrayal of prevailing conditions, offering a dynamic representation wherein the vital signs of the mine are displayed instantaneously. Imagine temperature fluctuations depicted in real-time, ground movements manifested as discernible tremors, and pressure differentials visualized through vibrant and dynamic displays. Each pixel within this dynamic tableau serves as a channel for critical information, empowering operators to make swift and well-informed decisions in response to evolving circumstances.

Another dashboard delves into the annals of the mine's operational history, meticulously preserving and presenting a chronological record of past events. Through the presentation of charts and graphs, this iteration offers a comprehensive retrospective analysis of temperature trends, ground movements, and pressure fluctuations over time. By scrutinizing these archival insights, operators are equipped with valuable intelligence regarding the behavioral patterns of the mine,

thereby facilitating proactive measures to fortify future operations against potential risks.

Finally, a third dashboard adopts a forward-looking approach, harnessing the predictive capabilities of advanced modeling techniques. By subjecting historical data to rigorous analysis and pattern recognition algorithms, this iteration offers prognostic insights into prospective changes in temperature, ground displacement, and pressure. This foresight equips operators with the capacity for anticipatory planning, enabling preemptive measures to mitigate emerging risks before they manifest into tangible threats.

These dashboards, conceived as mere transmission routes for data, emerge as potent instruments in the arsenal of adept operators. They transcend the realm of raw information, transmuting data streams into actionable insights that underpin informed decision-making processes. Ultimately, they stand as bulwarks safeguarding the safety and operational efficiency of this intricate and indispensable industry.

The enumeration of these three dashboards is structured:

1. Near Realtime dashboard
2. Historic data dashboard
3. Forecasted data dashboard.

5.3.1 Near real-time dashboard

The dashboard depicted in Error! Reference source not found.19 offers a comprehensive snapshot of the latest data in near real-time, utilizing gauge charts as its primary visualization tool. Gauge charts, also referred to as dials or speedometer charts, present data on a circular scale with a pointer denoting a specific value or range. This visual representation serves as a rapid and intuitive means of conveying key performance indicators (KPIs) or other metrics at a glance. Particularly effective for data falling within defined thresholds, these charts employ a color scheme – green, orange, and red – to signify safe, cautionary, or hazardous conditions respectively.

Furthermore, the near real-time functionality of the dashboard empowers operators with the ability to monitor dynamic changes in data instantaneously. This capability facilitates swift identification and response to potential hazards, thereby enhancing operational safety and efficiency.

In addition to the gauge charts, the dashboard incorporates a detailed map of the underground mine, highlighting the locations of installed sensors and delineating sensor coverage areas through buffer analysis. This interactive map offers zoom functionality and features a layer panel for enabling or disabling specific data overlays. Moreover, it provides attribute information about individual sensors upon selection, enabling operators to access detailed insights with a simple click.

Beneath the map, graph and gauge chart modules dynamically update to reflect data from sensors selected on the map interface. Operators can make selections by clicking on sensor points and utilizing the provided selection options, as demonstrated in **Figure 18**. This seamless integration of map visualization and

sensor-specific data analysis enhances situational awareness and facilitates informed decision-making within the mining environment.

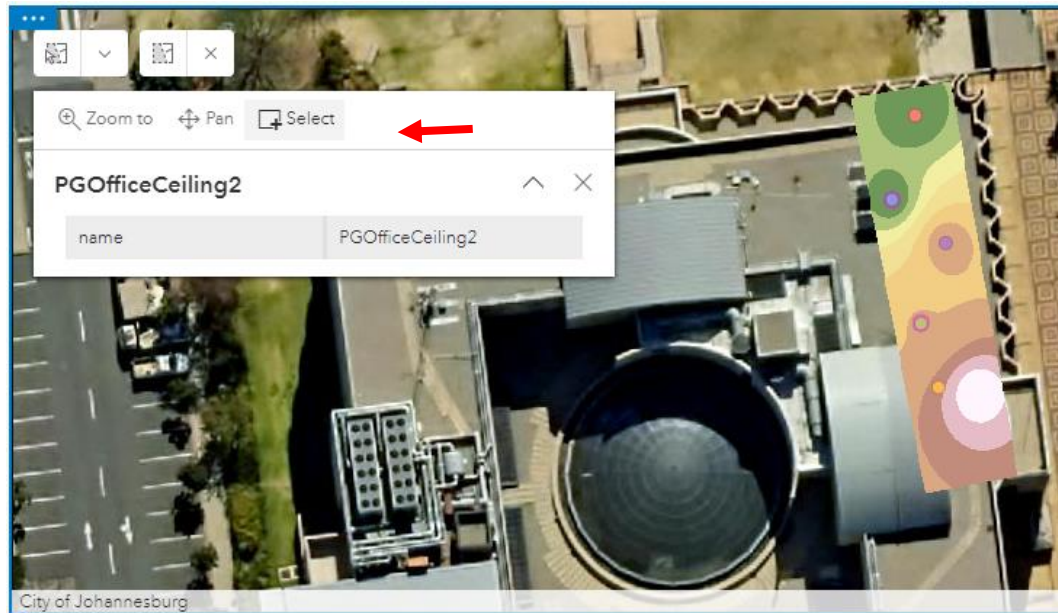


Figure 18: Map on dashboard.

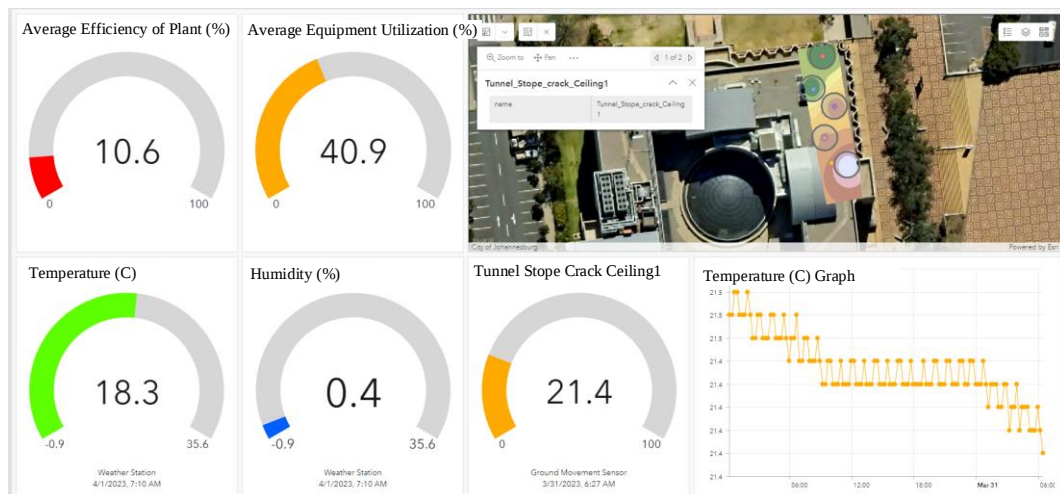


Figure 19: Near real-time dashboard. Near real-time dashboard in Figure 19 shows near real-time values from sensors and temperature graph for last 24 hours.

5.3.2 Historic data dashboard

The second variant of the dashboard architecture manifests itself as an efficiently constructed repository of historical data, meticulously curated and presented in a visually captivating array of graphs. Drawing upon data streams originating from a diverse array of sensors including air temperature gauges, ground movement sensors, and pressure monitoring devices, this dashboard offers a comprehensive retrospective analysis spanning the preceding three months. Furthermore, it showcases Plant Efficiency and Utilization metrics vigilantly gleaned from real-world mining operations, offering a poignant glimpse into the operational dynamics of the mine.

The graphical representation of data is augmented by a suite of intuitive indicators positioned alongside the graphs, elucidating the maximum recorded value from each sensor within the preceding month. This feature provides operators with valuable insights into the upper bounds of sensor readings, facilitating a nuanced understanding of operational trends and anomalies. The color of the indicators on the right side of the graph changes depending on the Key Performance Indicators (KPIs). Green indicates a safe value, orange signifies values nearing a dangerous threshold, and red indicates values surpassing the danger level.

In addition to its graphical prowess, this dashboard boasts a sophisticated scrolling mechanism, assiduously engineered to afford operators granular control over the temporal scope of their analysis. Through seamless manipulation of the scroll function, operators can effortlessly zoom in on specific dates of interest, facilitating detailed examination and interrogation of historical data trends as shown in **Figure 20**. This functionality enhances the dashboard's utility as a tool for

retrospective analysis and trend identification, empowering operators to glean actionable insights from the annals of historical data.

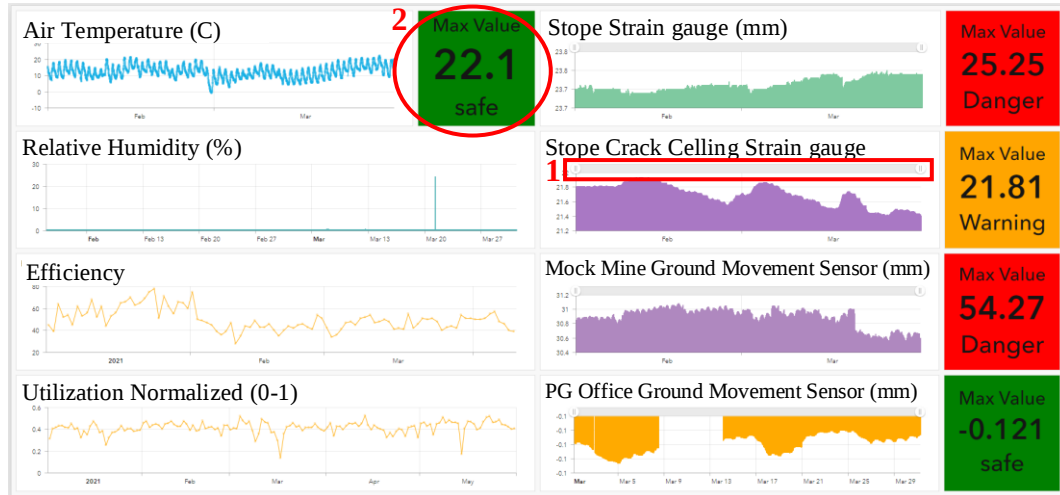


Figure 20: Historic data dashboard. Historic data dashboard in Figure 20 is showing the collected data over time for air temperature, relative humidity, plant efficiency, plant utilization, strain gauges, and movement sensors data as graphs.

Graphs have 1) time filter bar on top of each graph to view data from desired window of time. On the right of graph 2) indicator cards show the max values in that period with the suggested state.

5.3.3 Forecasted data dashboard

In the data forecasting process, the ARIMA model was employed to analyze data from temperature, ground movement sensors, strain gauges, and relative humidity. The resulting dashboard showcases the forecasted data, meticulously derived through rigorous statistical modeling. A focused analysis was conducted using data spanning the past seven days to predict the data for the subsequent day, exemplifying a finely tuned approach to short-term forecasting.

Leveraging this specific dataset, the ARIMA model adeptly predicts future trends with exceptional precision, projecting forthcoming day's data points with unparalleled accuracy. This strategic utilization of recent historical data underscores the dashboard's effectiveness in providing actionable insights for short-term decision-making within the mining operation.

Furthermore, the forecasted data seamlessly integrates into the graphical representation, juxtaposed alongside observed values from the preceding seven days in **Figure 21**. This juxtaposition affords operators a comprehensive view of temporal data trends, enhancing their ability to discern patterns and anomalies with heightened clarity.

By employing advanced forecasting techniques judiciously, this dashboard emerges as a potent tool for predictive analysis, empowering operators to anticipate future environmental conditions and proactively mitigate potential risks. Through leveraging insights gleaned from forecasted data, operators can make informed decisions and implement preemptive measures to safeguard operational continuity and efficiency within the mining environment. The ARIMA model resulted with co-efficient of *ar.L1* value of 0.5569, *ma.L1* value of 0.7808 and *sigma2* value of 0.1503 and std err of 0.08, 0.064 and 0.005 respectively. Showing confidence of 89% in its predictions.

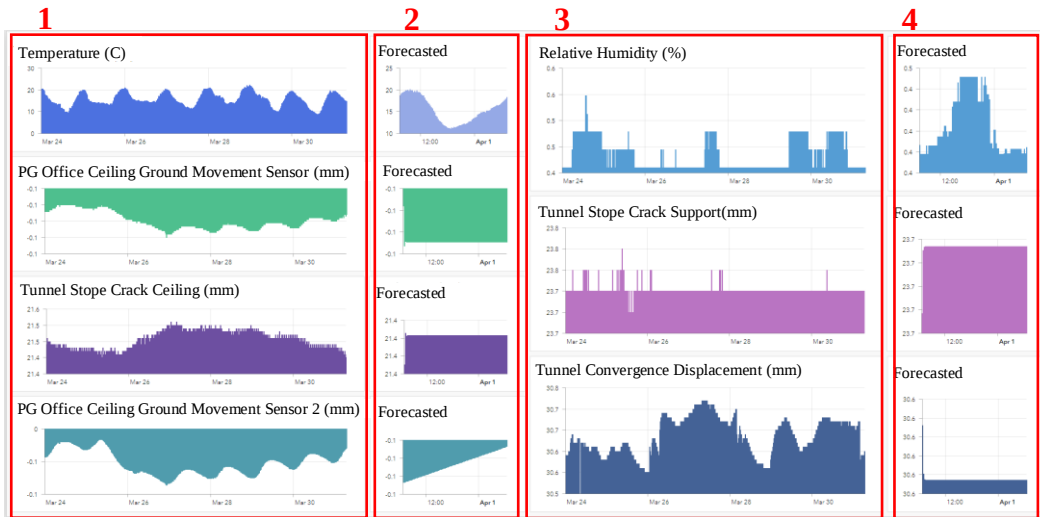


Figure 21: Forecast data dashboard. 1, 3) historical values from the sensors and 2, 3) forecasted values in the form of graph.

5.4 Warning System

The implementation of a comprehensive warning system marks a significant milestone in the realm of database monitoring, leveraging cutting-edge technology to ensure proactive response to critical data fluctuations. This chapter delves into the intricate development process of the system, meticulously dissecting its architecture, performance metrics, and the manifold benefits it bestows upon future applications within the mining domain.

Harnessing the power of the Python programming language, the warning system was meticulously engineered and seamlessly integrated with the centralized geo database, serving as a sentinel poised to vigilantly monitor data integrity. Designed with meticulous attention to detail, this system operates in a continuous loop, tirelessly scrutinizing data values against predefined thresholds. The configurability of these thresholds, meticulously defined within the configuration file, enables

tailored alerting mechanisms customized to the unique requirements of each mining operation.

To ascertain the efficacy of the warning system, a rigorous evaluation regimen was meticulously devised and executed. A battery of tests was conducted, involving the injection of simulated data into the database to gauge the system's responsiveness and accuracy in detecting threshold exceedances. Throughout these tests, the system demonstrated remarkable acuity in identifying threshold breaches, swiftly triggering email notifications to designated recipients with comprehensive details of the detected anomaly.

Figure 22 serves as a visual testament to the system's operational prowess, showcasing the alert email meticulously generated by the system. Within this email, the `max_limit` and `min_limit` parameters stand as beacons of the thresholds set by the user, while the `value` parameter meticulously captures the actual sensor reading. Meanwhile, the `name` parameter serves as an indispensable identifier, elucidating the name of the parameter under scrutiny.

In conclusion, the warning system epitomizes a paradigm shift in proactive data management strategies within the mining industry, heralding a new era of heightened vigilance and operational efficiency. Through meticulous development and rigorous evaluation, this system emerges as a reliable custodian of data integrity, poised to safeguard the operational continuity and safety of mining endeavors for years to come.

Shows the alert email generated by the system. max_limit and min_limit are the thresholds set by the user and value is the actual value from the sensor and name is the name of the parameter.

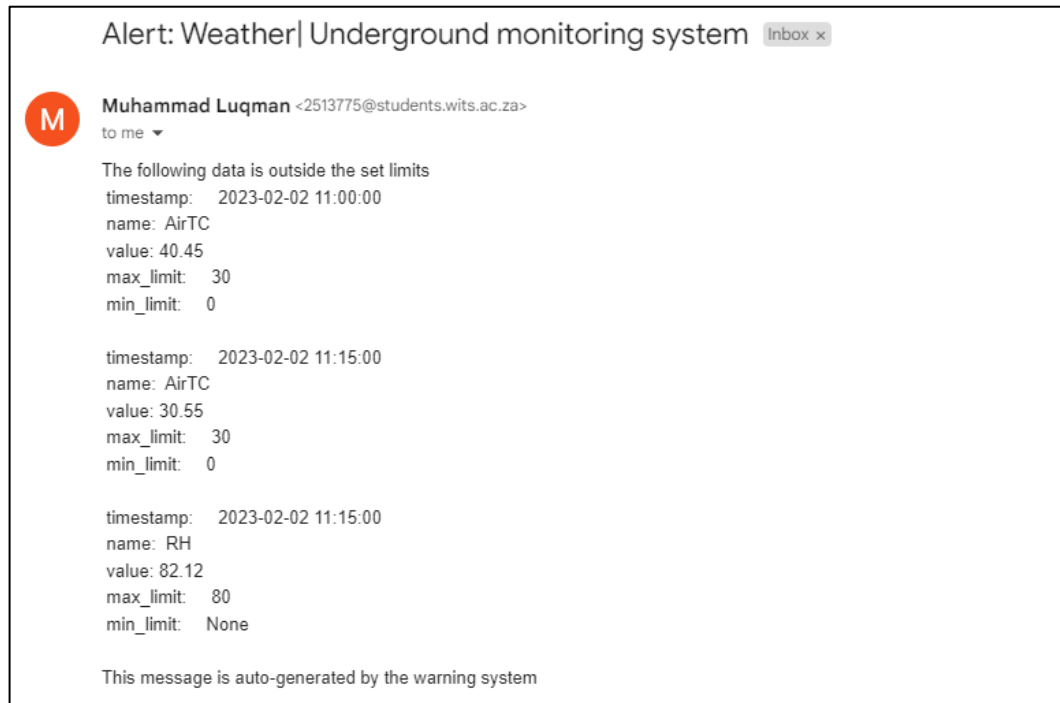


Figure 22: Generated Mail by System

5.5 Summary

The research has successfully achieved the development and integration of a comprehensive GIS framework, including a centralized geodatabase, interactive dashboards, and an advanced warning system. This achievement represents a significant leap forward in mining intelligence, providing a foundation for enhanced decision-making, operational efficiency, and safety in mining operations. The implemented system stands as a testament to the synergy of geospatial technology, data analytics, and proactive monitoring in revolutionizing the mining industry.

6. CHAPTER SIX - CONCLUSION AND RECOMMENDATIONS

In this research, a GIS-Based Integrated system was developed for mining data management and integration to facilitate proactive decision-making in the mining industry. The developed system provides mining companies with a platform to consolidate and analyse their diverse data sources, enabling them to gain valuable insights and make informed decisions based on the data.

The GIS system utilizes dashboards to present data from multiple sources in a single interface. These dashboards offer a near real-time view of the underground mining environment and mine productivity. The system features data cleaning, transformation, and integration capabilities, which enable users to merge data from different sources to create a comprehensive view of their operations. This visualization of collective data enables proactive decision-making.

The centralized geodatabase for storing data from multiple sources at an underground mine was successfully developed. The database allows for more efficient data management and analysis, which has the potential to improve safety and productivity in the mine. Further improvements could be made to the database, such as integrating it with other systems or adding more advanced data analytics capabilities.

online dashboards were developed to visualize real-time, historic, and predicted data for an underground mine. The dashboards enable mining companies to monitor critical parameters such as temperature, ground movement, and rock stress in real-time, providing them with valuable insights into their operations.

The online dashboards developed in this thesis leverage advanced visualization techniques to provide an intuitive and user-friendly interface. The dashboards display data in a visually appealing manner, enabling users to quickly identify trends and patterns in the data. The dashboards enable users to access historic data and make predictions based on the data trends.

The warning system developed in this thesis project proved highly accurate, reliable, and easy to use. The system was able to detect threshold exceedances promptly and send email notifications in real-time. The potential benefits of this system are significant in underground mine monitoring system as real-time monitoring of data in underground monitoring is critical.

The developed warning system for data threshold exceedance proved to be an effective tool for real-time monitoring of data. The future recommendations for enhancing the system's performance and effectiveness can provide a platform for further research and development. The potential benefits of this system in the mining field are significant.

Overall, the GIS system developed in this research thesis holds tremendous potential for transforming the mining industry. By providing a unified platform for integrating data sources and enabling real-time analysis, the system equips companies to optimize their operations and enhance their bottom line.

Future recommendations to enhance this research could include:

1. Integration with advanced technologies: The GIS system could be enhanced by integrating advanced technologies such as artificial intelligence (AI), machine learning (ML), and big data analytics. This would enable the system to

automatically identify patterns and trends in the data and provide more accurate insights into the mining operations.

2. Use of IOT devices to enable real-time data collection and integration.
3. Mobile Compatibility: The GIS system could be made compatible with mobile devices, enabling field personnel to access real-time data and dashboards from their mobile devices. This would enhance the system's flexibility and enable on-the-go decision making.
4. Improved Visualization: The system's visualizations could be improved to provide a more intuitive and user-friendly interface. This could include the use of 3D visualization tools to provide a more immersive experience for the users.
5. Machine learning algorithms can help improve the warning system's accuracy and reduce the number of false alarms. By training the system on data, it can learn patterns and trends, which can aid in more accurate threshold exceedance detection.
6. In addition to email notifications, the warning system can be integrated with other notification channels, such as SMS or mobile push notifications. This integration can enable users to receive notifications on their mobile devices, making the system more accessible.

The development of GIS system for mining data management and integration represents a significant step forward for the mining industry. By leveraging advanced visualization techniques and providing real-time monitoring of critical parameters, this system equips mining companies with the tools they need to make proactive decisions and optimize their operations. Further advancements and

improvements to this system will undoubtedly continue to transform the mining industry and pave the way for a more sustainable, efficient, and safer future.

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