

Innovative Approach for Monitoring Underground Excavations at San Xavier Underground Mine Laboratory

Nilufer B. Akbulut, Angelina Anani, Leonard D. Brown, Edward C. Wellman

The University of Arizona, Tucson, Arizona, USA

Copyright 2023 ARMA, American Rock Mechanics Association

This paper was prepared for presentation at the 57th US Rock Mechanics/Geomechanics Symposium held in Atlanta, Georgia, USA, 25-28 June 2023. This paper was selected for presentation at the symposium by an ARMA Technical Program Committee based on a technical and critical review of the paper by a minimum of two technical reviewers. The material, as presented, does not necessarily reflect any position of ARMA, its officers, or members. Electronic reproduction, distribution, or storage of any part of this paper for commercial purposes without the written consent of ARMA is prohibited. Permission to reproduce in print is restricted to an abstract of not more than 200 words; illustrations may not be copied. The abstract must contain conspicuous acknowledgement of where and by whom the paper was presented.

ABSTRACT: Assessing and making decisions in underground mines is crucial and is difficult due to the harsh environment and the limitation of accessibility. Monitoring plays an important role in assessing ground conditions to ensure safety and efficiency. Through consistent monitoring, a safe interoperable underground mine can be achieved, but to ensure coherent and valid monitoring, there are factors that need to be considered. The approach taken for monitoring with technologies used in it can highly impact the safety, productivity, and understanding of ground conditions. Visualizations designed with principles of Human-Computer Interaction (HCI), can improve knowledge, and aid situational awareness. Focusing on monitoring systems and interfaces that are user-friendly and reliable can help improve overall underground conditions. This paper proposes a monitoring framework that uses desktop and Virtual Reality (VR) to display rock movement in the San Xavier (SX) Underground Mine Laboratory through a digital twin.

1. INTRODUCTION

Continuous monitoring is required to enhance assessment and situational awareness (SA) in engineering projects such as mining. Monitoring creates a safer workplace, ensuring efficient and continuous production that meets production and profit goals. An optimal monitoring system for large-scale projects would be a system understood by different subject matter experts with varying levels of expertise. Continuous and efficient monitoring plays a foundational role in harsh and uncertain underground mine conditions. The data obtained from monitoring the rock mass in underground mine operations improves decision-making process, enhances the understanding of the current state of the mine, and helps make predictions. With the overwhelming flow of data, there is a higher possibility of having false positives and uninformative data representation, leading to serious cognitive burden (Zhou et al., 2017). The display of data and information and monitoring network design is crucial to overcoming cognitive burden. A monitoring system that emphasizes user-friendly methods, such as visual analytics (VA), would help engineers and workers gain insight from large and complex data sets resulting in enhanced overall SA (Zhou et al., 2017). Having a monitoring system that considers the display of information at an underground mine could secure the safety of the workers and minimize

risks, help to plan better designs, and evaluate current designs, and improve the advancement at the mine.

Slope stability monitoring in open pit mines ensures a safe operating mine, resulting in monitoring guidelines (Sharon & Eberhardt, 2020). However, to our best knowledge, a systematic monitoring system design, that begins with a network layout of sensors and instrumentations and ends with a user-friendly display, is limited for underground mines. The current state of monitoring in underground mining is conducted through engineers and workers visually assessing the working areas, using software with limited visualizations and interactions. This is done with very few real-time digital twin implementations of underground machinery (Wang et al, 2018). Compared to similar industries such as civil engineering and construction, similar challenges are observed where monitoring at long ranges with a coherent system that focuses on user-friendly representations seems to be absent (Wynne, 2022). This gap informs our proposed framework for near-real-time monitoring of underground rock mass with a digital twin representation. We focus on monitoring rock movement in underground mining operations.

1.1 Monitoring Rock Movement in Underground Mines

Continuous near-real-time monitoring of rock movement has a positive impact during the advancement of underground excavations and assessment in the rock mass characterization for future development. The harsh

conditions and production demands of underground mines result in time limitations to make the assessment of ground conditions. Additionally, underground environmental effects may reduce the situational awareness of the engineer and miners. Advancement and rock support can be hindered depending on the scale of the movement hindering productivity. Unexpected rock movement can result in unplanned support methods and production delays, affecting the overall mine plan. Through monitoring, we believe engineers can be informed of movements and even predict them, resulting in being able to prepare in advance and change the mine plan accordingly. This results in efficient production while meeting the financial goals of the mining company.

Even though monitoring can give engineers a larger perspective while minimizing unexpected hazards and costs, there are more factors that need to be considered during monitoring. Monitoring in underground production can give large quantities of data, making it hard to interpret. Thus, to ensure that the monitoring can have an impact on safety and productivity, we should consider innovative technological tools that follow Human-Computer Interaction (HCI) principles. Safety, and efficiency, during production, can be aided by monitoring rock displacement in digital twins. Digital twins are replicas of physical processes, working systems, or machinery and equipment components, matching the process, system, or machinery in question in real-time (Batty, 2018). It enables data to be transmitted from the real physical world to the digital world (Saddik, 2018). Digital twins help us understand environments and systems as a whole, and make correlations between datasets, which enhances the SA of the ground conditions. The range of cues a human focus on reduces, especially under stressful conditions (Dirkin, 1983). Therefore, having information and data displayed through one medium, such as a digital twin, is beneficial to the cognition tunneling of the user by eliminating the visualization of multiple graphs and datasets all at once.

Visualizing rock movement using digital twins aids the understanding of rock conditions and enables real-time assessments using visual and immersive analytics. The ability to gain knowledge remotely from digital twins can minimize risks and the chances of enduring hazards. The holistic approach of underground mine digital twins can improve the planning and design of future work. The varying data collected from monitoring can be further analyzed with information science. Information science is used to understand the correlation between monitored parameters, and the prediction of future rock displacements, advancing early warning and safety protocols.

1.2 San Xavier Laboratory Mine Case Study

Our framework of monitoring will be implemented at the San Xavier mining laboratory (SX), considering the end-

user, following HCI principles in the creation of the digital twin. The SX is owned and operated by the University of Arizona located in Arizona, south of Tucson. There are two main sets of underground workings. Primary production of up to 50 tonnes per day of lead, zinc, and silver ore took place between 1880 and 1952. A new decline is being developed by UArizona with 4.5m x 4.5m dimensions. The decline has advanced approximately 150 m, developed by using modern methods with a two-boom jumbo, and a rock bolting machine. Future development is being planned where it will be used as a testing ground for equipment, machinery, and research in the Mining and Geological Engineering department. The monitoring system proposed by this study will be implemented at the new decline as a part of a Ph.D. research supported by the mining and geological department. The entrance of the new decline is seen in Figure 1.2.1. in the orange ellipse, with the future direction of advancement shown in the orange arrow towards the Southeast.

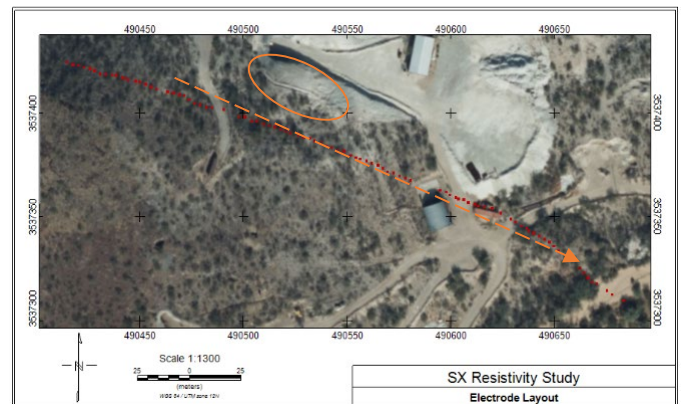


Figure 1.2.1. Map of new decline and electrode layout of resistivity study line at the SX (plan view).

The new decline is in concha limestone which comprises the bulk of the mine's footwall while the Angelica Arkose forms the hanging wall for the deposit. It is worth noting that there is no development drifting or access in the Arkose. Two possible clay-altered faults were discovered with a geophysical resistivity study and seem to have a strike in the Northeast direction with an unknown dip direction and angle. These structures are consistent with a mapped thrust fault. The electrode layout for the resistivity study can be seen in Figure 1.2.1 in red points, parallel to the advancement direction of the new decline. Future advancements of the new decline will intersect these faults, as seen in Figure 1.2.2., where the faults are shown in red ellipses.

The Concha formation is a fine-grained, medium- to thick-bedded limestone with gray to light-gray color containing lenses and nodules of chert and is moderately jointed to blocky and seamy. The limestone is weak and has average strength, with typical hardness values ranging from R2 to R3. The unconfined compressive strength (UCS) ranges from 16-40 MPa. In the new decline, the Rock Quality Designation (RQD) ranges from 0 to 80.

The rock mass rating (RMR) indicates poor to fair rock ranging from 30-50. The Q values range from 1-10. In the lower segment of the decline, strongly to highly altered versions of the limestone have been observed. This rock has an Index hardness value ranging from R1-R2, with no rock quality. Estimated strengths are on the order of 1-2 MPa, using Schmidt hammer values. The Q values range from 0.05 to 0.2. Excavations in the new decline are in low cover ranging from 3 m at the portal to a current maximum depth reaching around 20 meters. Given the ground conditions and the two faults, during future excavations, rock movement on the ribs and the roof of the underground opening, more specifically convergence may be expected.

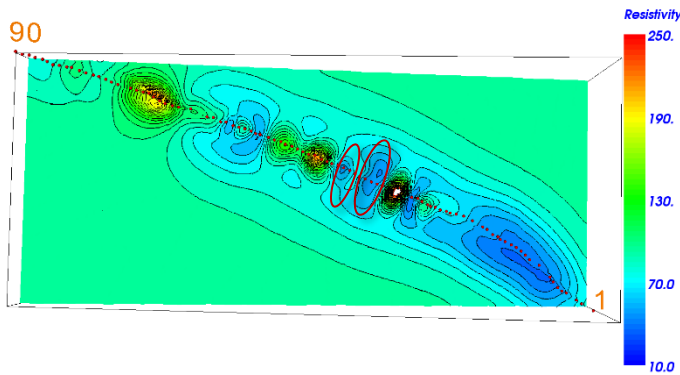


Figure 1.2.2. Faults from resistivity study with a Wenner array (plan view)

Currently, the rock support design consists of rock bolting and meshing. The 8 ft long Swellex bolts are placed in 1 to 1.5 m spacing on the ribs and roof, along with wedges that may cause potential failure resulting in rock fall. The bolts support sufficient support for the yield zone and a welded wire mesh with 10 cm x 10 cm (4-in x 4-in) holds rock fall. Rock blocks typically range from 5cm x 5cm rocks to 50cm x 50 cm in the limestone.



Figure 1.2.3. Image of expansion bolts after expansion with water pressure and 3'x3' mesh near portal at the SX

Discontinuities consisting of faults and joints are observed in the excavated areas of the mine workings at the SX. When considering old excavations and the results of rock convergence in the rock mass due to faults, along

with the faults that will be excavated through the new decline, we have determined to focus our monitoring on the rock movement of the ribs and the roof in relation with the rock mass, pore pressures, and potential climate effects.

2. METHODOLOGY

Our framework for a monitoring network design and implementation at the SX laboratory is being done in five main stages, (i) determination of parameters to be monitored, (ii) planning and design of monitoring network, (iii) installation of monitoring network, (iv) data acquisition and elaboration, and (v) display of monitoring data in the digital twin. Our logical framework covers all five stages mentioned above. Taking these steps can ensure a consistent data flow for the monitored parameters, enabling us to create a virtual environment and update it in near-real-time.

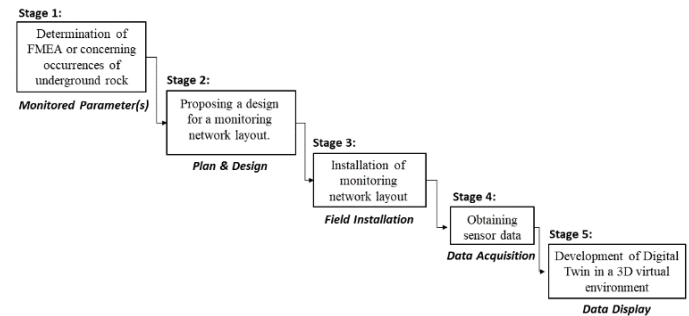


Figure 2.1. Logical Framework for Monitoring

As this project is ongoing research, in this paper, the data acquisition stage is a proposed method that will be conducted in future work before developing a complete and functioning digital twin, a prototype has been created. This paper will mainly focus on stage 1 – determination of parameters to monitor, and stage 2 – planning and design of a monitoring framework, where information and implementations of other stages will be given in more detail in future work.

2.1. Determination of Parameters to Monitor

Our first stage in the framework focuses on choosing the correct parameters to monitor to ease the second stage, planning, and design of a monitoring network and have an overall successful monitoring design. Which dependent parameter to observe in a physical system can be chosen by determining whether it is causing risks and hazards, disrupting the safety and production. While creating a monitoring system for geotechnical purposes in underground mining, there are different aspects of geomechanics that needs to be considered. Geotechnical occurrences and failures are related to the rock mass characteristics while being stimulated by on-site conditions, excavation processes, and hydrogeological conditions (Clero, 2022).

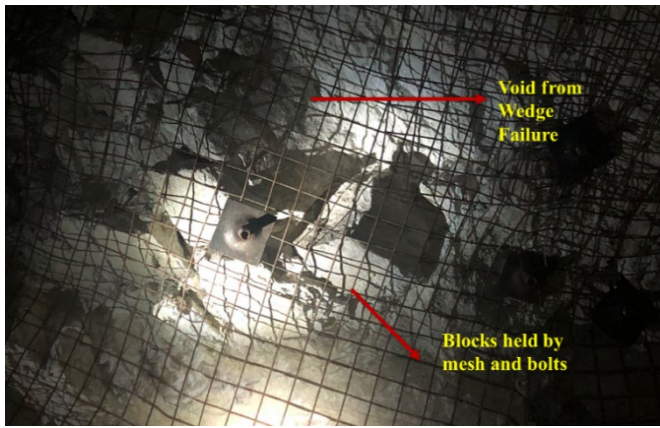


Figure 2.1.1. Picture of wedges in the rock mass on the roof

Many discontinuities including joints, fractures, and faults have been observed starting at the entrance of the decline to the face, where the latest excavation occurred in 2021, along with the two major faults with clay alterations, found through a geophysical resistivity study. There are many rock falls in ranging sizes that occur regularly at the new decline. If an area of possible rock fall hazards is highly jointed with small dimensions of rocks, the mesh is being used to support it, while if an area consists of wedges formed by joints in larger sizes of rocks, a rock bolt will be used to prevent a wedge failure resulting in rock fall. Potential rock falls from wedges formed by the discontinuities, can be seen in Figure 2.1.1. The new decline is relatively a near-surface excavation where water precipitates through the rock from the surface to the roof with heavy rain in monsoon seasons. Future excavations that will take place with drill and blasting coupled with changes in pore pressure can play a role in rock movement and/or rock falls. Even though signs of water in Figure 2.1.2 are not seen in the deeper parts of the decline, there is a possibility of water buildup in the rock mass.



Figure 2.1.2. Signs of water precipitation on the walls at the SX
To classify the instabilities at the new decline, we used the classification method proposed by Kaoutar Clero et al, in 2020, to ease the determination of the monitored parameter. While classifying geotechnical instabilities,

we have taken into account old openings as well since the structural geology and rock mass conditions are familiar to each other. The progressive instability happening overtime at the SX is the rock movement, especially in openings where a fault has passed through. The immediate instability happening in a short time at the SX is rock fall. After the classifications, we made further analyses with Failure Mode and Effect Analysis (FMEA), where failure modes or occurrences are identified with their causes and effects (Rousand, 2004) to understand the risks of these instabilities. Before implementing a monitoring system, we believe conducting an FMEA of the specific mine is the first crucial step of our proposed framework. We created a risk matrix both for rock movement and rock fall to finalize our focus on monitored parameters following a Failure Modes, Effects, and Criticality Analysis (FMECA) (Rousand, 2004), seen in Figure 2.1.3., where;

- 1 - Rock Movement in the current state
- 1*- Rock Movement in future advancements
- 2 - Rock Fall in the current state
- 2* - Rock Fall in future advancements.

Severity \ Probability	Minor	Major	Critical	Catastrophic
Frequent		1*	2*	
Probable			2	
Occasional	1			
Remote				
Very Unlikely				

Figure 2.1.3. Risk Matrix of Rock Movement and Rock Fall at the SX.

While creating the risk matrix, the old openings were also observed and analyzed due to the rock mass having the same conditions and behavior as the new decline, helping us to determine what to expect in future advancements. From Figure 2.1.3., the expected instabilities at the SX mostly fall under high-risk, expected with further excavations.

2.2. Plan and Design of a Monitoring Network
The logical framework for the plan and design stage focuses on selecting sensors, instrumentations, and equipment and designing their layout in the zone of the openings. For the new decline, we aim to monitor the movement of the rock on the ribs and roof with two arrays of sensors, a load cell sensor, and Lidar scans. The new decline has a split section with two faces for future advancements. A new design is being planned for the face looking in the south direction, where advancement will take place in the southeast direction, as shown in Figure 1.2.1. The strength of the rock mass around the split section decreases due to the wider design of the opening. As this section is near the surface, the yield zone of the

stress distribution can exceed rock matrix boundaries, creating the possibility of surface subsidence in the future. Blast propagation from future excavations might affect the failures caused by fractures, through microcrack failures in the rock mass that is already jointed, causing a penetrating failure near the split section (Qiu, 2022). These failures can also have an impact on the other face, where far future excavations will be conducted. Therefore, as an initial step, we have created two arrays of sensors that consist of MEMS and vibrating wire (VW) sensors, placed in the wider section of the split section, and near the face on the ribs and the roof, a load cell (LC) placed in the roof of the split section as shown in Figure 2.2.1., where the arrays are shown with red lines on the plan view. Along with the sensors installed to measure the rock mass parameters, regular Lidar scans are being used to acquire point cloud data. Using varying sensors and

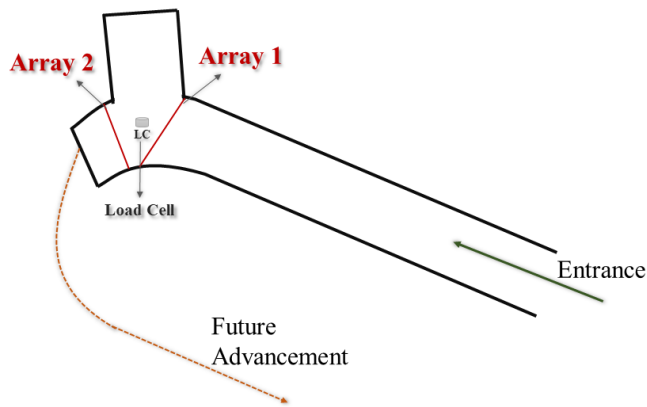


Figure 2.2.1. Placement of sensor arrays in split section and opening (plan view).

Lidar scans or photogrammetry in underground mining is not rare, but to our knowledge, there is no guide or framework focusing on the relation between the varying datasets acquired. Along with innovative methods, such as Lidar scanning with drones, there still seems to be a heavy reliance on traditional monitoring methods. In underground engineering, traditional methods and assessment by individuals require monitoring to be executed manually, exposing personnel to dangerous environments (Wang, 2020). Due to the reasons stated above, the planning and design of our monitoring network focus on using sensors along with other traditional methods, to overcome the current monitoring limitations and to automate the monitoring system.

In stage 1, the focus of the monitoring was determined to be rock movement to raise situational awareness and increase the assessment of ground conditions and instabilities. In relation to rock movement, the parameters to measure in our physical system are strain, stress, vibration, 3D orientation in space, temperature, and pore pressure of the rock. Due to the conditions at the SX, mentioned previously, future work will consider the correlation between these datasets, such as rock displacement relation with increased rock mass

temperature and pore pressure. The sensors acquired for these measurements can be seen in Table 2.2.1.

Sensors	Measurement	Raw Data	Parameter
VW Strain Gauge	$\mu\epsilon$	Hz	Rock Strain
VW Load Cells	$\mu\epsilon$, kg	Hz	Rock Stress
MEMS	mm	V (Volt)	Rock Disp.
VW Thermistor	$^{\circ}\text{C}$	Hz	Rock Temp.
VW Piezometers	kPa	Hz	Pore Pressure

Table 2.2.1: Sensor Acquired

(i) *VW sensors* are commonly used in varying industries, with successful applications of them in civil engineering. This is due to their resistance to temperature and potential to decrease interference, making them withstand long durations in harsh environments (Wang, 2020). In an underwater tunnel case study, VW strain gauges (SG) were used for strain measurements to monitor the deformation of the walls, where the strain gauges have been installed for longer than 3 years with more than 80% of them being in working conditions (Yang, 2018). Another case study, long-term monitoring of large caverns, used VW sensors due to their advantages over linear potentiometric (LVDT) sensors (Sudhakar, 2020). Due to their performance in harsh conditions, long life spans, and their integrability in rock bolts, we selected VW sensors for monitoring.

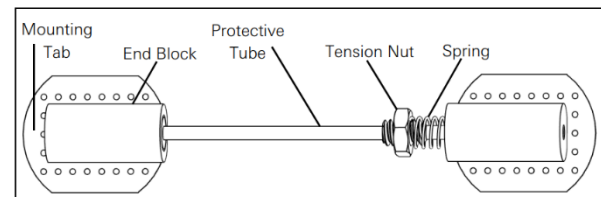


Figure 2.2.2. VW SG Model 4100 developed by Geokon.

(ii) *MEMS accelerometers* differ from other types of accelerometers by measuring acceleration on surfaces using a capacitive method which has the capability to measure static and dynamic response in three directions, X-Y-Z (Kulkarni, 2019). They have been prevalently used for geotechnical monitoring over the years (Wang, 2020), such as for automatic geodetic monitoring (Danisch, 2008). We have integrated MEMS sensors into our framework in the light of the monitoring tool Cir arrays, developed by ASE s.r.l., from their basis on Modular Underground Monitoring System (MUMS) technology, (Segallini & Carini 2013; Segalini, 2014). We were highly influenced by the case studies done for monitoring road tunnels with Cir arrays (Savi, 2019; Carini, 2019). The biggest disadvantage of MEMS sensors is their sensitivity to heat changes ranging from 10 $^{\circ}\text{C}$.

(iii) *Lidar Scanning* is a typical approach to mapping an underground mine, capturing the 3D point cloud data, where data points are defined with their X-Y-Z coordinates in a 3D Cartesian coordinate system, sometimes capturing intensity and color (RGB) information depending on the sensor used (A.S Rao et al., 2022). Laser scanning is usually done on a stationary platform, but innovative methods are also being implemented in underground mines, such as handheld or mounted on vehicles. For our mapping of the rock movement, we will use the Hovermap LiDAR developed by Emenset, with its feature to attach to a backpack that a person may carry. This feature enables the monitoring process to be done while a staff or engineer is making visual assessments, easing the process of scanning and data acquisition. The layout of the sensor network on the ribs and roof can be seen in Figure 2.2.3 and Figure 2.2.4.

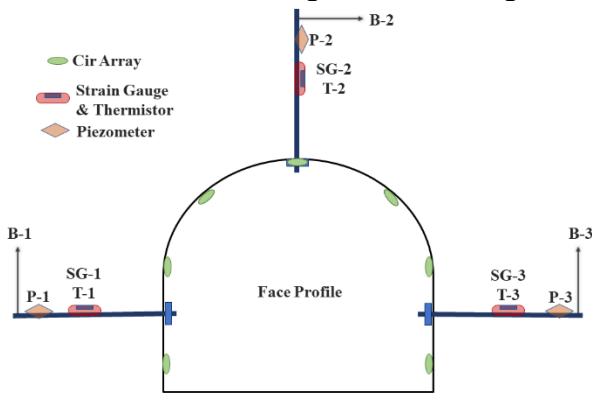


Figure 2.2.3 Sensor Network Layout for Advancing Face

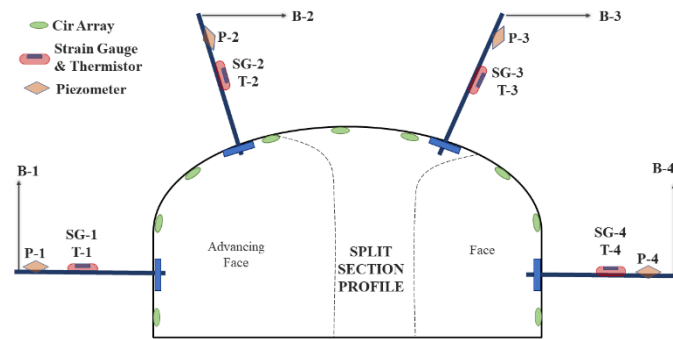


Figure 2.2.4 Sensor Network Layout Split Section

To ease the installation stage the SG that are weldable will be implemented on rock bolts, to measure the strain in the rock mass. Each SG comes with its VW thermistor, further easing the process of measurement of rock mass temperature. To incorporate monitoring into daily operations at an underground mine, this framework aims to achieve an easy and cost-effective installation method. Therefore, implementing sensors onto bolts can save time by installing monitoring sensors into the rock mass while the support is being installed. The LC for the split section will be implemented onto the rock surface on the roof through bolting (figure 2.2.5). The Geokon VW Load Cell Model 4900 is used. Instrumentation for acquiring the data from the sensor arrays have been given in Table 2.2.2., where instrumentation is referred to as equipment

and instruments used for monitoring other than sensors or mapping sensors. The SX laboratory mine already has an advanced wireless Wi-Fi network system with multiple nodes ensuring large area coverage. Due to the already existing network for IoT at the SX, and the complex technology behind it, we will not discuss it further.

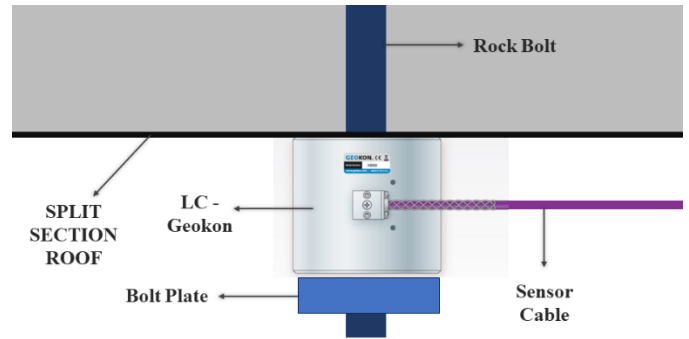


Figure 2.2.5 Geokon VW LC Model 4900 installation on roof

Instrumentation	Use Cases
Datalogger	Receives raw data from VW sensors and transfers them to a database with a Wi-Fi network
Multiplexer	Ensures data acquisition from more VW sensors
Signal Converter	Converts signals from sensors to ensure the datalogger can receive the data

Table 2.2.2 Monitoring Instrumentation

Since the project is still in its installation phases, we will briefly go through stage 3, field installation at the SX. To incorporate sensors in a time effective matter, as we mentioned before, the sensors will be installed on bolts, but the SX used expansion bolts which this step becomes difficult. Due to this challenge, we will be using split set and dewidag type rock bolts. The cable management from the sensors could be done either through the mesh installation or mine hooks that are already used for electrical cables, etc.

2.3. Data Acquisition and Elaboration

After the data collection, we plan to analyze the data of the rock mass to be incorporated into the digital twin. The digital twin will incorporate near real-time raw data as well. The main goal of the fourth stage in the framework is to create knowledge and extract data with a comprehensive method, which can be used for daily assessment of ground conditions, decision support, and future predictions through intensive data analysis. To showcase the complex nature of rock conditions at a 24/7 operating underground mine, an approach that values interoperability should be followed. The logic for this goal is similar to BIM (Building Information Modelling or Managing) processes. BIM is dominant within the construction industry where 3D, real-time, dynamic modeling software is used to analyze data of complex

structures (Kubba, 2012), while they are seen as a fundamental development for future smart cities (Fu, 2018). We aim to have an interoperable dynamic 3D model in a virtual environment using digital twin innovation and use them for future smart mines. For this stage, data analysis, simulation modeling, and visualization and the steps between these components, illustrated in Figure 2.3.1., need to be thought out thoroughly, for future decisions.

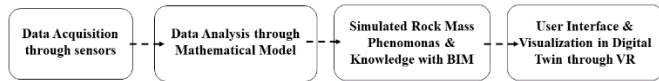


Figure 2.3.1 Components of Stage 4 and Stage 5

A dynamic simulation needs near-real-time data collection and integration, making this stage, of data acquisition a challenging and computing-intensive part of modeling (Akhavian, 2012) and monitoring. The timeliness of data acquisitions will highly depend on the second stage of the proposed framework where the instrumentation and the selection of sensors has a role in the automation process of monitoring. For instance, selecting a datalogger that is compatible with the implemented sensors along with Wi-Fi to ensure connection to IoT and cloud systems, eliminates manual data acquisition and transmission done by personnel. For an uninterrupted flow of input data from the physical world to the digital twin, the third stage of the monitoring framework needs to be done precisely and managed well considering the environment where the installation takes place. This can include the maintenance of an installed network. When the timeliness of data elaboration is considered, there are other factors that ought to be thought of, like data analyses of the monitoring measurement. For instance, using edge computing, to achieve input data that is fit for a dynamic digital twin, will increase the speed of data elaboration and data transmission. This project will consider using edge computing technology for future improvements. The current plan for stage 4 considers the data being classified, analyzed, and modeled with a cloud system through a database where raw data is being stored. For a digital twin to be a dynamic tool that simulates rock behavior as close as possible to the real-world system, the computing rate of modeling rock mass behavior and the behavior being updated on the digital twin accordingly needs to be considered for future work.

2.4. Creation of a Virtual Digital Twin

The first four stages of our proposed framework enable the efficient flow of data from various sensors (e.g., strain gauges, accelerometers, etc.) to front-end tools. Although simple dashboards may be used to generate reports or render graphs of the raw data, these simple visualization techniques are often insufficient to meet the challenges of the heterogeneous datasets required for monitoring and analysis tasks in underground mines. While engineers are technically good at interpreting sensory data (Tomai,

2023), underground mine environments are different from most industries' working environments. Underground mines are hard to reach, thus limiting the accessibility of assessment of rock conditions. They are harsh environments that can inhibit the evaluation process of an engineer and limit their judgment. The time to make an assessment is short and decreased due to the installation of support for an ongoing excavation. More stable openings also can be hard to monitor since an engineer's focus can shift more to an ongoing excavation rather than observing and maintaining other areas of the mine. These conditions can decrease the situational awareness of the engineer and workers, cause work fatigue, and increase unnecessary multi-tasking. Digital twins can aid the assessment process by increasing the observability of underground rock conditions and contextualizing the data from sensors in spatially intuitive ways relative to the mine environment.

Digital twins also provide real-time, on-demand access to data streams, enabling new mechanisms to integrate sensor networks for real-time monitoring (Garcia, 2020). The technology can provide early warning for hazards or failures, enabling engineers to 'see it before it happens' with near-real-time data inputs. Digital twins also provide common ground to facilitate communication across different areas of expertise within a team (Gageldonk & Weterings, 2019). Challenges to developing effective digital twins include gaining access to data, interfacing with analytical tools, and visualizing multiple sources of data through the lifecycle of a project (Garcia, 2020). To address these issues, we envision a digital twin that superimposes sensor data onto a multi-scale, interactive 3D model of the mine environment. Our digital twin will coordinate and contextualize data streams using the 3D model, allowing users to intuitively explore relationships among these data at variable scales and levels of detail. To enable our digital twin, we are developing a new framework which includes a data integration and rendering pipeline as well as a front-end, interactive prototype.

Data Integration and Rendering Pipeline

Numerous computational challenges must be overcome to develop a variable-scale, 3D digital twin. First, data must be acquired and transformed for real-time display in a virtual environment that enables acceptable framerates for interaction and scales reasonably well as new sensor networks are added. As our virtual environment may contain hundreds or thousands of sensors and millions of data points representing the mine environment, a high-performance transformation and rendering engine is required. As a foundation for our digital twin framework, we are using the Unity development environment (www.unity.com), a real-time creation platform for 2D, 3D, and Extended Reality (XR) applications.

To streamline the flow of information into our Unity-based digital twin, the virtual environment will be rendered using point cloud data from Lidar scans, as opposed to photo-realistically textured meshes of polygons. Point clouds have different file extensions depending on the Lidar scanner manufacturer; although Unity can natively read files of numerous formats (for example, .fbx, .3ds, .dxf, and .obj), additional transformation steps are needed to pre-process these point clouds into 3D representations that may be rendered in real-time (e.g. data formatting, density reduction, transformation to world space, etc.). Our data integration pipeline is outlined in Figure 2.4.1. Notably, our implementation approach allows the virtual environment to be efficiently updated as the mine changes and new Lidar data are acquired.



Figure 2.4.1. Data integration pipeline for digital twin.

Color palettes (RGB) are used to visually encode regions of point cloud data in the 3D model, allowing users to more easily orient themselves and identify locations within the virtual mine environment. Furthermore, dynamic heatmaps may be used to animate changes in conditions over time in the virtual environment based on the observations collected in real-world geo-space at the mine. Unity's Lightweight Render Pipeline (LWRP) enables low latency rendering to achieve the palettization and heat mapping effects; LWRP is a high-performance scriptable rendering pipeline for defining rendering algorithms that run efficiently even on lower-end devices. Future work will focus on data-oriented design to utilize the processor cache to increase performance, using Unity's DOTS (Data Oriented Technology Stack).

Prototype Development

To maximize the utility of the digital twin for collaborative analysis and monitoring tasks, intuitive visualizations are needed that make the sensor data easy to explore and easy to understand. We propose a variable-scale digital twin with dynamic scaling capabilities, allowing users to zoom out to understand context and zoom in to examine localized changes in sensor data. This interaction design is shown in Figure 2.4.2. At the highest level, users may observe the entire mine environment, using color palettes to distinguish specific mine sections, declines, and other labeled features, as well as heat maps to identify areas of significant change. At the lowest level, the digital twin enables users to experience a first-person "life-size" view of the virtual mine and to observe readings from individual sensors or sensor networks.

Studies further suggest that visualizations of digital twins may be enhanced by XR technologies (Tao et al., 2019).

Furthermore, XR-based multi-scale visualization has been shown effective for collaboration with complex datasets (Hua, Brown, & Gao, 2004). We are developing user interfaces for our digital twin that will work on desktop computers and also benefit from the additional immersion capabilities afforded by virtual reality (VR) head-mounted displays (HMD).

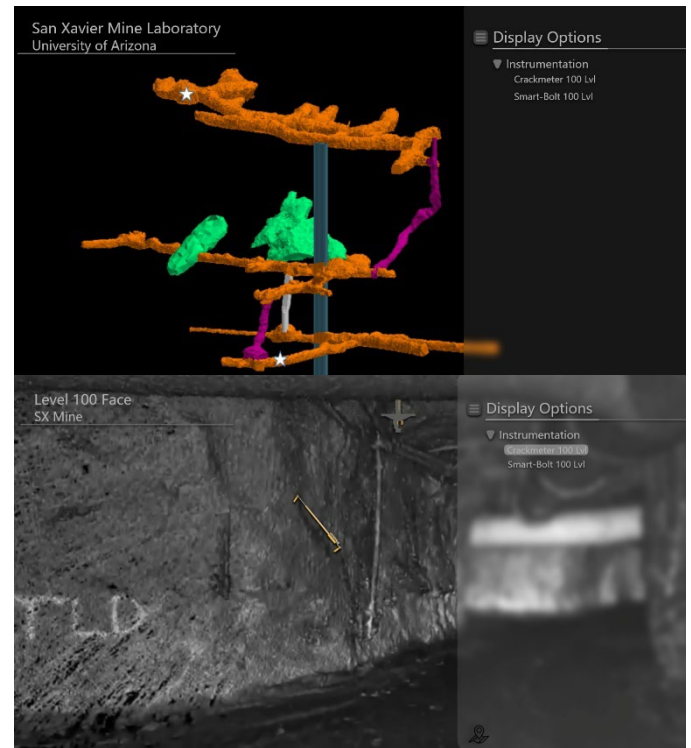


Figure 2.4.2 Prototype digital twin with variable-scale display. Top: High-level view showing context of mine; Bottom: Low-level view showing first-person view of individual sensors.

3. RESULTS AND DISCUSSION

The contribution of the presented framework has been to provide a systematic guideline that can be used for monitoring underground mines and to consider engineers in the usability of the monitoring information through a digital twin of the rock mass. To our best knowledge even though there are innovative approaches for underground monitoring, this paper gives a holistic approach to accessing multiple datasets while displaying them via an intuitive visual interface using digital twins. Every mine site is different with unique factors that will affect all the stages of this framework, therefore we tried to give detailed descriptions of these stages for it to be adaptable to different cases. Unfortunately, there may be underground mines that may not be able to implement this framework, since the 'one size fits all' metaphor is not possible in the varying possibilities of underground mines. Monitoring underground can also vary depending on its use case. Monitoring rock mass at an ongoing production for a cut and mine will highly differentiate from monitoring rock mass around the draw bells of a

block caving mine, but the FMEA can help engineers decide with ease unrelated to the mining method.

The planning and design stage will have a strong foundation due to the selection criteria provided in the first stage. Basic knowledge of what measurements are needed ensures the right selection of sensors, mapping techniques, and instrumentation. Underground workers and geotechnical engineers already understand the mine and its concerning areas. The next effort will be made in the direction to plan the placement of monitoring methods as needed. With variations in underground mine occurrences and hazards, the support system with its tools will highly vary. Therefore, the installation of sensors into the rock mass as we proposed, might be a challenge, and unique methods might need to be discovered to do so, which may result in our proposed design not being possible due to time constraints and installation techniques. Giving the approach taken for the design of sensors can give some insight into other use cases. Current modern mines mostly have either a radio mesh network or Wi-Fi network for communication. This provides a high chance for mine sites for acquiring data but the automation process through data transmission to the IoT in a cloud system might be eliminated depending on the communication line used. This will also inhibit the dynamic simulation of a digital twin. Digital twins and their creation require heavy technical knowledge from multiple disciplines which makes them hard to develop. Therefore, the display of data can be achieved through other methods such as web-based dashboards, the display of data points on 2D maps, or a representative static digital twin, whether it may be developed by engineers or a third medium.

4. CONCLUSION

The Underground mining environment is challenging due to production demands and variable ground conditions. Most engineers and technicians can see a small subset of collected data. As a result, it takes most geotechnical practitioners years of experience to develop sound engineering judgment to make good decisions on ground support and advance mine development.

HCI concepts and the development of digital twins allow engineers to collaborate, review the same data sets, make relations and extract information. This is done by allowing a team of engineers to look at the same sets of information in real time. This allows young engineers and technicians not only the opportunity to collect data but to collaborate with experienced senior professionals in the Digital twin to see how informed geotechnical decisions can be made. Geotechnical Monitoring and data collection can be a time-consuming task. Then processing the data and using it for mining decisions is a complicated

process involving multiple expertise areas. For this reason, developing an HCI tool and digital twin can benefit the mining industry. Once more fully developed mining companies can incorporate it into the daily cycle of underground mine production. The goal is a comprehensive collaboration framework in a digital twin for safe production for the full mining cycle.

Lastly, underground mines face highly complex engineering problems that require advanced solutions proposed by people. Therefore, the role of miners in the decision-making and problem-solving process can be made easier by adopting the concept of making information more available using the concepts outlined in this paper.

References

1. Andrew Tomai, (2023). Delivering a Real-world application using azure digital twin. Retrieved from: <https://learn.microsoft.com/en-us/shows/internet-of-things-show/delivering-a-real-world-application-using-azure-digital-twin>
2. A. Carri, A. Valletta, A. Segalini, R. Savi (2019). On-site applications of innovative tools for deformation monitoring in underground excavations. *ISRM AfriRock - Rock Mechanics for Africa*, Volume 2017-October, 2017, Pages 579-592
3. A. Carri, L. Chiapponi, R. Savi, A. Segalini (2017). Innovative technologies for monitoring underground excavations during construction and usage. *ISRM International Symposium "Rock Mechanics for Africa", Vol. Symp. Series S93, Cape Town, South Africa*.
4. A. El Saddik (2018). Digital Twins: The Convergence of Multimedia Technologies. *IEEE MultiMedia*, vol. 25, no. 2, pp. 87-92, Apr.-Jun. 2018.
5. Ashvini K., Augusta S. B. P., (2019). Statistical analysis of accelerometer, gyroscope with state estimation. *Intl Journal of Engineering and Advanced Technology (IJEAT)* Volume-9 Issue-1S3, Dec. 20.
6. A. Segalini, & C. Carini (2013). Underground landslide displacement monitoring: a new MEMS based device. *Landslide Science and Practice*, Vol. 2: Early Warning, Instrumentation and Monitoring, 213: 87-93. Berlin: Springer.
7. A. Segalini, L. Chiapponi, B. Pastarni, C. Carini, (2014). Automated inclinometer monitoring based on micro electro-mechanical system technology: Applications and verification. *Landslide Science for a Safer Geoenvironment*, Vol. 2: Methods of Landslide Studies, 1 January 2014: 595-600.
8. Aravinda S. Rao, et al. (2022). Real-time monitoring of construction sites: Sensors, methods, and applications. *ScienceDirect Automation in construction*
9. Batty, M. (2018). Digital twins. *Environment and Planning B: Urban Analytics and City Science*, 45(5), 817–820

10. Dirkin, G. R. (1983). Cognitive Tunneling: Use of Visual Information under Stress. *Perceptual and Motor Skills*, 56(1), 191–198.
11. Feng Fu, Chapter Six - Design and Analysis of Complex Structures, Butterworth-Heinemann, (2018). Pages 177-211.
12. Geokon (2021). A geotechnical engineer's guide to MEMS accelerometer specifications (Part 1 terminology). Retrieved from: <https://www.geokon.com/Session-01>
13. Guido van G., Pieter W., (2019). Digital twins: The power of a virtual visual copy. Unity Unite Copenhagen 2019. Retrieved from: <https://www.slideshare.net/unity3d/digital-twins-the-power-of-a-virtual-visual-copy-unity-copenhagen-2019>.
14. Helen S., Jennifer P., Yvonne R., (2019). Interaction design: beyond human-computer interaction, 5th edition pg 1-34.
15. Hua, H., Brown, L.D. & Gao, C. (2004) "SCAPE: Supporting Stereoscopic Collaboration in Augmented and Projective Environments." *Computer Graphics & Applications*, Vol. 24: 1. IEEE Press, p. 66-75, 2004.
16. J.P. Yang, W.Z. Chen, M. Li, X.J. Tan, J.X. Yu, (2018). Structural health monitoring and analysis of an underwater TBM tunnel *Tunnelling and Underground Space Technology*, vol. 82, pp. 235–247, 2018.
17. Kirill F., Nursultan A., Ekaterina U. Manuel M. (2020). A case study on object-oriented and data-oriented design paradigms in game development.
18. Lee D., Adam C., Jason B., Maciej B., (2008). Fusion of geodetic and mems sensors for integrated monitoring and analysis of deformation. 13th FIG symposium on deformation measurements and analysis, 4th IAG symposium on geodesy for geotechnical and structural engineering, LNEC, Lisbon 2008 May 12-15.
19. Lixin Wang et al. (2020). Automatic monitoring system in underground engineering construction: Review and procpoect. *Hindawi Advances in Civil Engineering* Volume 2020, Article ID 3697253.
20. Lunardi, P. (2008). Design and construction of tunnels Analysis of controlled deformations in rocks and soils (ADECO-RS). Springer Verlag: Berlin 2008.
21. Marvin Rausand, A. Høyland (2004). System Reliability theory models, statistical methods and Applications, 2nd edition pg. 88-96.
22. M.J. Kavvadas, (2005). Monitoring ground deformation in tunneling: Current practice in transportation tunnels. *Engineering Geology* 79 (2005): 93-113
23. Patricio Gonzalez V., Jen L., (2015). The Book of Shaders. Retrieved from: <https://thebookofshaders.com/01/>
24. Qian Wang, Min-Koo Kim, (2019). Applications of 3D point cloud data in the construction industry: A fifteen-year review from 2004 to 2018, *Advanced Engineering Informatics*, Vol 39, 2019, Pg 306-319.
25. Reza A., Amir H. B. (2012). Integrated data collection and analysis framework for remote monitoring and planning of construction operations. *Advanced engineering informatics* 26 (2012) 749–761.
26. Roberto S., Andrea C., Edoardo C., Alessandro V., Andrea S. (2019). Application of innovative monitoring tools for safety and alert procedures in road tunnels. 13th International Scientific Conference on Sustainable, Modern and Safe Transport (TRANSCOM 2019), High Tatras, Slovak Republic, May 29-31, 2019
27. R. Said, Andronic B., Achalhi M. (2022). Monitoring of geotechnical instabilities at deep underground mines, case of Draa Sfar mine, Morocco. *Proceedings of the 7th World Congress on Civil, Structural, and Environmental Engineering (CSEE'22) Lisbon, Portugal Virtual Conference – April 10 – 12, 2022*
28. R. Sharon, E. Eberhardt (2020). Guidelines for Slope Performance Monitoring 1st edition. Pg 10-170.
29. Sam Kubba (2012). Chapter 5 - Building Information Modeling, Editor(s): Sam Kubba, *Handbook of Green Building Design and Construction*, 2012, Pg 201-226.
30. Sandra M., Crystal G., (2020). Leveraging Unity in the new age of digital twins. Unity Unite 2020. Retrieved from: <https://resources.unity.com/unitenow/online-sessions-to-inspire/leveraging-unity-in-the-new-age-of-digital-twins>
31. Sudhakar, K., and S. R. Naik (2019). Long-Term Stability Monitoring of Underground Cavern Using Geotechnical Instrumentation - A Case Study. Paper presented at the 14th ISRM Congress, Foz do Iguaçu, Brazil, September 2019.
32. Van Der B., J.P., Clayton, C.R.I., Powell, D.B., (2003). Displacements ahead of an advancing NATM tunnel in the London clay. *Géotechnique* Vol. 53 Issue 9, November 2003: 767-784.
33. Qiu, J., Feng, F. (2022). Effect of Different Tunnel Distribution on Dynamic Behavior and Damage Characteristics of Non-Adjacent Tunnel Triggered by Blasting Disturbance. *Mathematics* 2022, 10, 3705.
34. Y. Guo, H. Wang, Q. Hu, H. Liu, L. Liu, M. Bennamoun, Deep learning for 3d point clouds: a survey, *IEEE Trans. Patt. Anal. Mach. Intell.* 43 (12) (2020) 4338–4364.
35. Zachariah Wynne, Tim Stratford, Thomas P.S. Reynolds (2022) Perceptions of long-term monitoring for civil and structural engineering, *Structures*, Vol 41, 2022, Pg 1616-1623.
36. Zhou, F. et al. (2018), Visually enhanced situation awareness for complex manufacturing facility monitoring in smart factories, *Journal of Visual Languages & Computing*, Vol. 44, 2018, Pages 58-69.
37. Fei Tao, Meng Zhang, A.Y.C. Nee (2019), Chapter 11 - Digital Twin and Virtual Reality and Augmented Reality/Mixed Reality, Editor(s): Fei Tao, Meng Zhang, A.Y.C. Nee, *Digital Twin Driven Smart Manufacturing*, Academic Press, Pages 219-241.