Transforming geotechnical decision-making using the internet of things and data analytics

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The increasing availability of the Internet of Things sensors is driving a rapidly growing desire for real-time monitoring systems, resulting in the generation of much larger volumes of data. Rock engineering departments are faced with the need to process more and more data and are expected to draw insights and to make decisions based on this data but often with fewer resources and less available time. Fortunately, many software packages are now available to assist the rock engineer with processing and analysing vast volumes of data in order to draw meaningful insights. These packages have the capability of data management, data processing, analytics and even machine learning and artificial intelligence. However, with so many software options available, including instrument specific software, in-house developed packages, as well as many software solutions focused specifically on geotechnical applications, how does the rock engineer make the right choice?

Groundwork Consulting has been investigating, evaluating and developing software solutions for geotechnical applications for the past six years. During this time most of the software packages available worldwide specifically developed for visualising and analysing geotechnical data have been evaluated. This paper reviews the journey taken, the potential pitfalls, the lessons learnt and the current status of visualisation options for geotechnical applications. Three case studies are presented in detail to demonstrate the lessons learnt. These case studies are used to provide recommendations for rock engineers who are faced with the challenge of selecting and implementing software to gain insights into larger and larger volumes of geotechnical data. The paper is intended to assist rock engineers who wish to migrate from the use of spreadsheets for data management, data processing and visualisation but are unsure of which direction to follow. It also provides a road map for those in the industry who are expected to use software to gain insights and to make recommendations based on their geotechnical data, but who are uncertain where to find the most appropriate software solutions and how to maximise the benefit from them.

INTRODUCTION

Rock engineering has evolved into a multi-skilled profession which not only requires considerable knowledge and experience of theoretical and traditional methods, but also the need to adopt the latest technologies to make informed decisions. This is required to meet best practises but additionally to comply with the mining legislation set out in Section 11 of the Mine Health and Safety Act of 1996. Furthermore, the introduction of Mining 4.0-enabled data collection of multiple parameters at a rate never seen before in rock engineering, and different methods of data interpretation critical to rock engineering can be implemented with the use of these technologies (Zhu *et al.*, 2011). This has left rock engineers in the position where large quantities of data need to be processed, analysed, and converted into knowledge in order for accurate insights to be drawn and decisions to be made.

However, they face difficulties with regard to limited resource and expertise availability, with experts and research into actual data analytics for rock engineering being very limited in the rock engineering profession (Stacey, 2014).

Solutions do however exist to aid rock engineering departments with the adoption of Mining 4.0 and to meet Mine Health and Safety Act compliance requirements with multiple software packages available. The global geotechnical engineering software market is predicted to reach a market size of $4652 million by the year 2032 which constitutes a 320% growth from 2023 (Astute Analytica, 2024). With the rapid growth in this market segment, challenges arise for rock engineers around how to select the correct packages for specific operations and characteristics unique to the South African mining environment.

In order for rock engineers to select the correct packages, the Data, Information, Knowledge and Wisdom (DIKW) model and Industrial Internet of Things (IIoT) model provide insights into the objectives and outcomes required from software packages.

DIKW Model

The DIKW model provides a framework for rock engineers to navigate the complex landscape of data management and decision-making. By systematically transforming raw data into wisdom, the ability to make informed decisions, despite facing resource and expertise limitations can be enhanced. This model, reproduced in Figure 1, combined with the IIoT model in Figure 2, helps identify the objectives and outcomes required from software packages, ensuring that the chosen solutions effectively support the rock engineers' needs in data collection, storage, processing, and analytics. This structured approach is essential for rock engineers to keep pace with the rapid growth in geotechnical engineering software and the unique challenges of the South African mining environment.

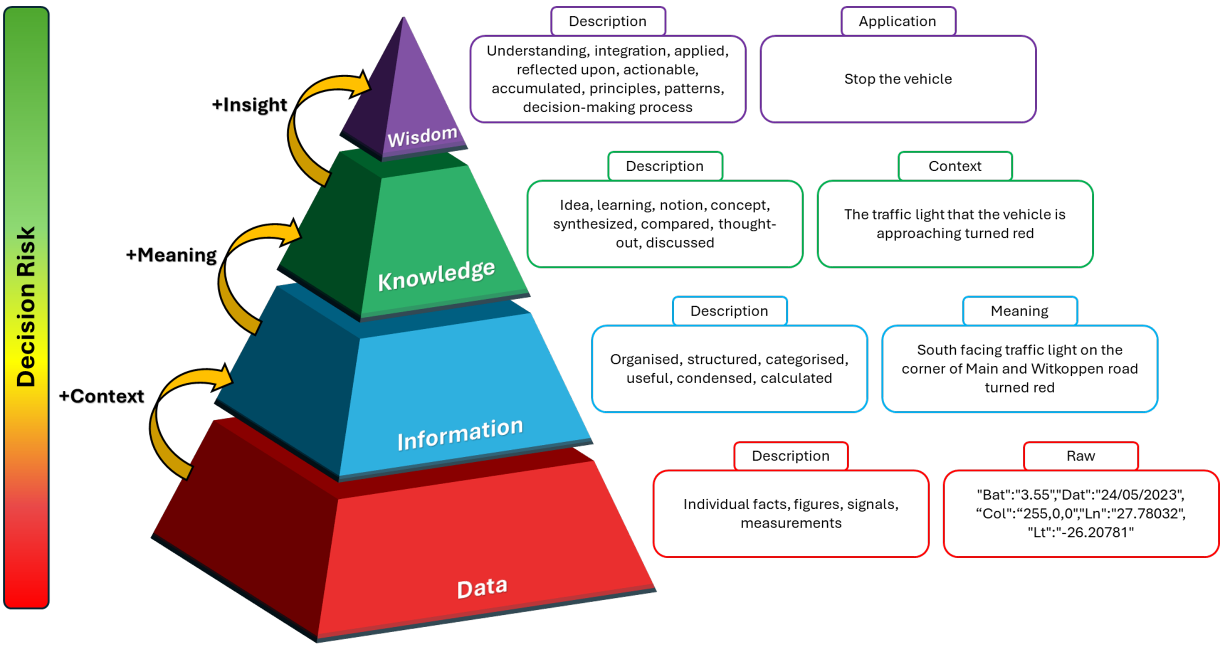

Figure 1. The DIKW model in pyramid form.

In a rock engineering context, data refers to the unprocessed facts collected from various sources such as ground movement, stope closure, stress, strain and seismicity. The data lacks context and meaning.

Information is derived by organising, processing and structuring the data to add context. This would include using software tools to analyse data and producing outputs such as graphs and visual representations. Information aids in identifying patterns, trends and anomalies in rock mass behaviour, providing a clearer picture for compliance and operational standards.

Knowledge is obtained by adding meaning to the information through interpreting and analysing the data and understanding the implications. This occurs by adding experience and expertise to make sense of the processed information. Knowledge aids rock engineers to understand and predict potential hazards and develop strategies for rock support and risk mitigation.

Wisdom is the ability to make informed decisions based on accumulated knowledge by adding insight to the knowledge. This results in strategic decision making to ensure safety, compliance and efficiency. Wisdom includes leveraging insights to anticipate future conditions, optimising processes and implementing proactive measures. By understanding the wisdom required, suitable software packages can be selected and continuously adapted to improve the end results required.

In addition to being able to select the correct software packages, rock engineers should also understand when data science, machine learning or artificial intelligence features are required.

Data Science vs Machine Learning vs Artificial Intelligence
There are key differences between data science (DS), machine learning (ML) and artificial intelligence (AI). In the context of the DIKW model, each technology fulfills a key parameter in the model.

- Data science produces insights and takes the place of information in the model.
- Machine learning produces predictions and takes the place of knowledge in the model.
- Artificial intelligence produces actions and takes the place of wisdom in the model.

Although the AI umbrella is complex, and machine learning in essence falls under the artificial intelligence branch, it is removed and simplified here as a function on its own for simplicity.

In an attempt to explain the difference between the roles of DS, ML and AI, an example using real-time sensors for monitoring and managing ground stability is given below.

Data science:

- Role: Gathering and processing raw data to derive meaningful insights.
- Example: Collecting data from various sensors installed in a mine to monitor parameters such as ground movement, stress, and seismic activity. Data scientists and software packages analyse this data to generate reports and visualisations that highlight patterns and anomalies in ground behaviour.
- Application: Using software tools to create heatmaps and time-series graphs showing areas of potential instability, providing a clear understanding of current conditions.

Machine learning:

- Role: Using processed information to make predictions.
- Example: Developing a machine learning model that predicts the likelihood of rock bursts based on historical data and current sensor readings. The model is trained on a dataset containing measurements of stress, strain, and seismic events from various mining sites.

- Application: Deploying the model to predict high-risk areas within the mine, enabling pre-emptive measures to be taken. For instance, the model might indicate an increased risk of rock burst in certain areas of the operation, prompting additional reinforcement or evacuation.

Artificial intelligence:

- Role: Taking informed actions based on predictions and accumulated knowledge.

- Example: Implementing an AI-driven control system that automatically adjusts mining operations in real-time to enhance safety and efficiency. The AI system uses predictions from the ML models to make decisions, such as altering the mining sequence or adjusting support systems to mitigate risks.

- Application: The AI system might autonomously decide to halt operations in a specific section of the mine when the predicted risk of a rock burst exceeds a certain threshold, ensuring the safety of workers and equipment.

Industrial Internet of Things model
The primary focus of this paper is understanding data science and analytics in order to aid rock engineers to select the correct visualisation and analytics software. The IIoT model captures the core parameters from the sensing level to understanding and analysing the data received. This is the foundation of implementing the DIKW model and is required before ML and AI can be implemented.

By focusing on the foundational aspects of the model such as sensing, networks, platforms, and interfaces the groundwork is laid for future integration of ML and AI technologies. The simplified IIoT model is presented in Figure 2.

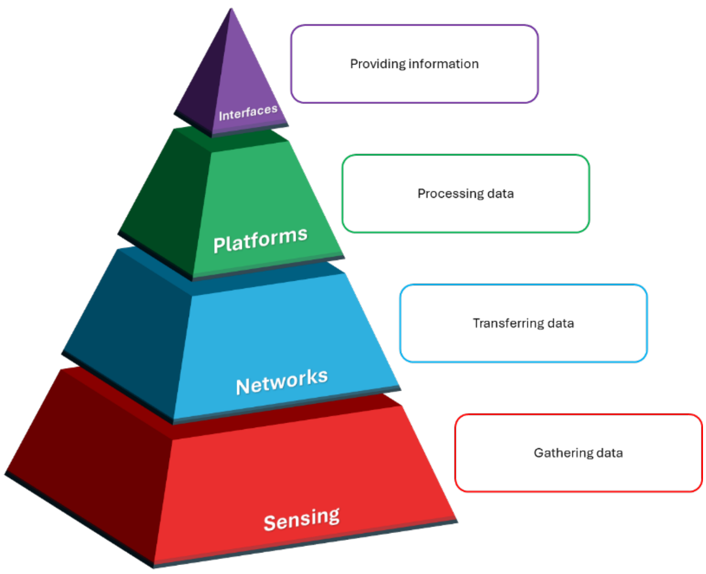

Figure 2. Simplified IIoT model.

Sensing:

- Context: The model begins with the deployment of sensors to collect raw data from various sources within the operation. This includes monitoring ground movement, stress, strain, seismicity, and other critical parameters.

- Objective: Ensuring comprehensive and accurate data capture to provide a solid foundation for subsequent analysis.

Networks:

- Context: The collected data is then transmitted through reliable and secure network infrastructures. This includes both wired and wireless communication systems or manual means of data collection that ensure data is efficiently transferred from the sensors or manual measurements to central processing units.

- Objective: Maintaining the integrity and availability of data during transmission, especially in challenging environments such as mining operations.

Platforms:

- Context: The data is stored, processed, and managed on robust analytics platforms. These platforms are equipped with advanced visualisation tools that convert raw data into understandable formats such as graphs, charts, and dashboards.

- Objective: Facilitating rigorous data analysis and enhancing comprehension through visual representation, making it easier to identify patterns and trends.

Interfaces:

- Context: User interfaces and reporting tools are designed to timeously present processed information in an accessible and actionable manner. This includes high-level alarm systems, real-time monitoring dashboards, and comprehensive reporting capabilities.

- Objective: Ensuring that the insights derived from data analysis are effectively communicated to decision-makers, supporting informed decision-making and operational efficiency.

These core components ensure data integrity and accessibility of data from the point of capture to the final presentation. By utilising the IIoT model, the key objectives and functionality of a software package become clear. By keeping the end in mind, software packages can be evaluated and suitable software packages can be selected in order to efficiently interpret data.

THE ROUTE TO FULL AUTOMATION BASED ON THE IIOT MODEL

In order to reach full automation in a monitoring system a phased approach is recommended. This approach will also eliminate considerable capital expenditure from the project onset. It is important to define what is currently available and what is required. Although the IIoT model has a sequence and building blocks, the model should be applied by keeping the end in mind at all times. Some projects might require a reverse approach where interfaces and platforms are selected first. By selecting the correct visualisation and analytics platform that is both versatile and expandable, the project can be tackled in the reverse order. Based on case studies and projects conducted by Groundwork Consulting, the following case study will provide clarity on this approach.

Case study 1 – Phased approach to automation

Background:

A mine located in South Africa required a system to monitor tunnel convergence. The mine had existing manual systems in place to monitor the convergence prior to implementing the new system. The current system included taking four manual measurements using a modified distance measurement device at multiple locations along the tunnel. This required hundreds of data points to be captured on a monthly basis. After taking the measurements at each location, the data was then transported by the field technician to surface where the rock engineer would manually enter the data into an Excel sheet. An Excel Macro was then used to process the data and visualise it in various chart formats. The Excel Macro had limited functionality and it was prone to crashing regularly. Groundwork Consulting were approached to identify or develop a system which met the following requirements:

1. Implement a cloud-based platform that records, stores, analyses and visualises the data received from the technician.

2. In-depth data analytics required to display data via heatmaps, line-graphs and overlayed images to enable data-driven decision making (DDDM).

3. Improve the methods of manual data capturing to improve data integrity.

4. Creation of multi-level alarming functionality.

5. Automated reporting on a regular basis.

6. Provision for both manual data capturing methods along with automated sensor data capturing.

If the IIoT model is implemented from the base upwards, the logical first step would be to determine the sensing hardware required to monitor the tunnel and then to automatically get the data flowing in order to analyse the data in real-time. The monitoring project would then ideally include the following components in order to fully automate the monitoring system:

- Measuring device – High resolution laser.
- Data recording – Data logger.
- Data extraction – Interface to remove data (manual/software).
- Data transfer – Routing of data from sensor to interpretation component (manual/network).
- Data storage – Local or cloud-based storage.
- Data processing – Software to automatically process the data to be interpreted later.
- Data visualisation – A local or cloud-based software to visually display the data.
- Data analytics – The same visualisation software used to provide in-depth data analytics.
- Data insight – From the analytics performed, insights can be made available and displayed over visuals.
- Alarms and notifications – From the data insight alarms and notifications can be triggered accordingly.
- Reporting – Software to combine analytics, insights, alarms and notifications to provide data that enables insight to the convergence.

In this project it was not financially feasible to equip the entire tunnel with sensors at each station. Furthermore, studies would have then been required to determine critical locations and only monitor critical locations, a task that would be meaningless without collecting valuable data from all locations to accurately determine critical locations.

Solution:

The proposed solution transitioned to an online data capture form with cloud storage, ensuring data validation and permanent storage. This streamlined data processing, improved accuracy, and integrated the data into a suitable visualisation platform for better analysis and decision-making.

It was found that a phased reverse approach in the IIoT model would be most effective initially. Hence the correct visualisation and analytics platform was selected in order to capture manual data and allow future automations to be integrated. This approach would benefit the mine in two ways. Firstly, all stations would be monitored without the use of sensors and secondly, the data could be analysed to determine the actual required stations to be monitored in an automated system. The system could also be implemented within a few weeks, as it adapts to the current procedures in place.

By selecting the correct interface and platform, valuable insights can be derived and visualised and other sensing methods implemented at a later stage once the critical stations have been identified. Controls were put in place to ensure data integrity via the platform. A simple user interface allowed for technicians to enter the data, freeing up time for the rock engineers, optimising the entire process.

A phased approach is strongly recommended and it can be implemented with various methods. The table below indicates different options available.

	Component	**Introductory**	**Basic**	**Intermediate**	**Advanced**	**Reverse approach**
Sensing	**Measuring device**	Manual	Sensor	Sensor	Sensor	Manual
Networks	**Data recording**	Manual	Data logger	Data logger	Data logger	Manual
	Data extraction	Visual	USB/Bluetooth interface	USB/Bluetooth interface	Node interface	Manual
	Data transfer	Manual	Tablet	Tablet	Network	Software
Platforms	**Data storage**	Excel	Excel	Software	Software	Software
	Data processing	Excel	Excel	Software	Software	Software
	Visualisation	Excel	Excel	Software	Software	Software
Interfaces	**Analysis**	Excel	Excel	Software	Software	Software
	Insights	Manual	Manual	Software	Software	Software
	Notifications	-	-	Software	Software	Software
	Reporting	Excel/MS Word	Excel/MS Word	Software	Software	Software

Table 1. Multiple approach methods using the IIoT model

A simplified system design approach is shown in Figure 3.

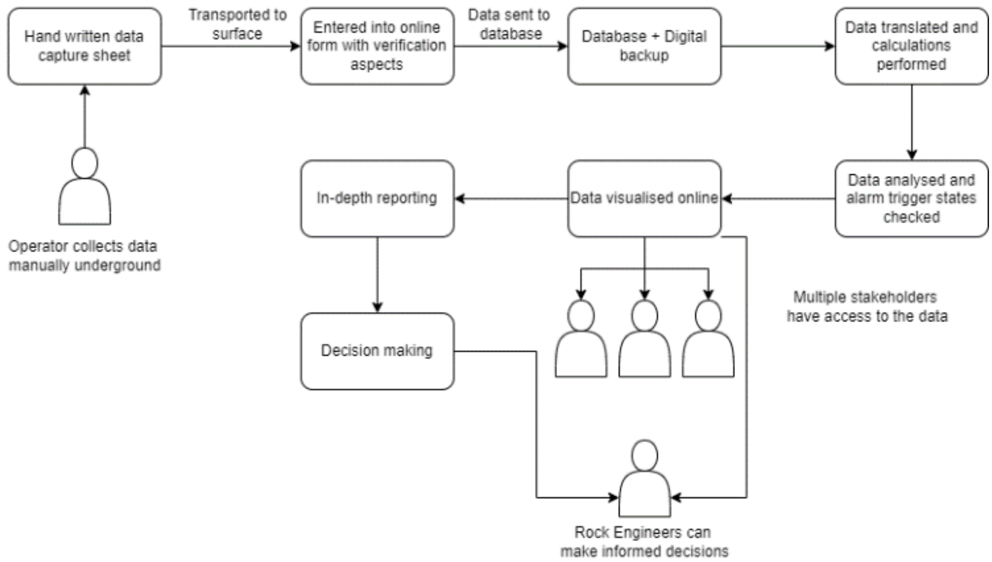

Figure 3. System design flow chart.

GEOTECHNICAL VISUALISATION SOFTWARE SELECTION

Selecting the correct geotechnical visualisation software is critical. If this process is neglected, companies can easily be locked into contractual agreements without receiving any benefits and, more importantly, not receiving valuable insights from data. As the migration to digital platforms takes time, the use of an incorrect platform will waste valuable time and resources. Based on our experience, the typical issues found with geotechnical visualisation platforms are listed below:

1. **Fragmentation:** Avoiding situations where different data sources and sensors require multiple visualisation platforms, leading to a loss of context. This also creates confusion as multiple platforms are used in conjunction with one another.

2. **Lack of integration:** Most platforms do not support inputs from multiple sources, preventing a comprehensive view of the data. This is typically found with vendor specific packages.

3. **User training and maintenance:** Each platform requires specific training and maintenance, adding complexity and overheads.

4. **Upgrades and maintenance:** Upgrades and maintenance requirements leading to downtime, introducing new bugs and additional training requirements.

5. **Cost:** Managing separate platforms for each sensor type can be expensive.

6. **Data discrepancies:** Stress, strain, load, and displacement data are often displayed on different platforms, complicating data analysis.

7. **Visualisation limitations:** Many platforms offer limited analytical capabilities, focusing only on data display without deeper insights.

8. **Historical data:** Some platforms do not support long-term data storage and retrieval, limiting historical analysis. Historical data is often in different formats requiring translation or parallel visualisation.

9. **Customisation challenges:** Adapting visualisation platforms to the users' specific needs can be difficult and time-consuming and is usually not an option for platforms which serve multiple customers.

10. **Error and redundancy:** Overlapping data points and manual data input can lead to errors and the selected platform should be resilient to known data issues that can occur.

11. **Alarms and notifications:** Basic alarm systems on superficial parameters without advanced predictive capabilities can lead to false alarms, degrading the trust in the platform.

Based on the pitfalls which have been experienced with numerous software platforms, the following requirements are deemed to be essential:

1. **Multi-data source integration:** The platform must accept inputs from various sources, including Excel sheets, automated IIoT sensors, manual data capture forms, and multiple sensors as well as multiple values from the same sensor.

2. **Robust data processing and analysis**: The platform should support data transformation, calculations, and advanced analytics to generate actionable insights from raw data.

3. **Configurable visualisation tools**: It should offer customisable visualisation options, for example heatmaps, image overlays, rate-of-change graphs, and other graphical representations to enhance data comprehension.

4. **Historical data access:** The platform must provide comprehensive historical data storage and retrieval, allowing for long-term analysis and trend identification.

5. **Advanced alarms and notifications:** It should feature advanced alarm capabilities, including predictive alerts based on historical and real-time data, to facilitate proactive decision-making.

6. **Data integrity and verification:** Strong mechanisms for data verification and validation are essential to ensure the accuracy and reliability of the data.

7. **Local and cloud storage:** The platform should support both local and cloud-based data storage solutions to ensure data redundancy, security, rapid data restoration and easy accessibility.

8. **Scalability and expandability:** It must be scalable to accommodate additional sensors and data types, and expandable to integrate future technological advancements.

9. **User-friendly interface:** An intuitive and user-friendly interface is crucial for ease of use, reducing the training requirements for stakeholders.

10. **Support and maintenance:** Reliable local support and maintenance services are necessary to address any issues promptly and provide ongoing training and system updates.

11. **Customisation and flexibility:** The platform should allow for customisation to meet specific operational needs and adapt to various mining conditions and requirements.

12. **Cost-effectiveness:** It should offer a cost-effective solution, balancing advanced features with affordable pricing to ensure accessibility and sustainability for the mining operation. Life-cycle costs must be determined.

13. **Track record:** A platform must be chosen which has at least 10 years of a successful operational track record to ensure that the majority of errors and bugs have already been eliminated.

PLATFORM LIMITATIONS AND CONSEQUENCES

It is clear that it is a difficult task to select the correct platform, and selecting the incorrect platform can not only have financial implications, but also display data incorrectly which leads to incorrect decision making and potential safety consequences. A recent case study conducted by Groundwork Consulting based on the IIoT model highlights the limitations and consequences of selecting the incorrect platform.

Case study 2 – Inadequate visualisation platform
Background:

A client required a mine-wide closure monitoring system to report in real-time and to be visualised accordingly. The mine had a condition that the data generated by these sensors should not leave the mine premises and that data management would be handled internally. The mine selected a visualisation platform to be hosted locally that would visualise and analyse the data.

Requirements:

1. Select and install IIoT closure sensors with a high resolution of at least 0.01mm.
2. Bridge IIoT sensors into the local network of the mine.
3. Provide software to capture data in JSON format from the sensors and to store it in a local directory on the mining network.

Based on the IIoT model, the mining company requested Groundwork Consulting to complete only the sensing and networks part of the model. The mining company took it upon themselves to handle the platform and interface part of the model.

As part of the hand-over procedure, the data was visualised by the sensor provider in order to match the data with that of the mining company. It became clear that the platform used to visualise the data was inadequate and had serious limitations. The following core functionality was missing from the platform:

1. Data visualisation was limited to 30 days and data beyond that point could not be visualised.
2. Basic alarm functionality was available on preset limits. No rate-of-change alarms were available. No advanced alarms could be generated.
3. Changes in JSON formats and updates to the system could not be handled by the platform.
4. Data could not be exported to other formats.
5. No reporting functionality was available.
6. Graphs could not be adjusted and there was no option to change x and y-axes.
7. The platform was slow and did not allow for any user changes to be made.

Solution:

The platform was deemed insufficient for depicting data correctly and did not provide an actual representation of the status of the ground. The solution is to run an advanced visualisation platform in conjunction with the current platform to highlight the pitfalls of the current platform as shown in Figure 4. The advanced visualisation platform included the following core functionality:

1. Multiple sensor type inputs including manual and IIoT sensors.
2. Advanced charting options with multiple configurations and selecting of x and y-axes values.
3. Comparing multiple sensors on a single chart.
4. Normalising data functionality.
5. Visualising multiple parameters of a single sensor on a chart.
6. Mapping functionality.
7. Advanced alarm functionality including offline and delayed parameters. Alarming functionality based on warning and trigger levels. Alarming functionality based on advanced calculations such as rate-of-change and velocity.
8. Data export options to CSV format for stakeholders via the platform.
9. Full historical view of data on the graphs.
10. Application programming interface (API) via the platform to ensure mining systems can integrate with the platform if automated control systems would like to be implemented with the data received and analysed.
11. Email notifications based on alarms.
12. Access to visualisation and analytics from any internet connected device anywhere in the world.
13. Permanent data storage.

The above points are seen as the minimum requirements that a platform should include in order to provide accurate insights into the data to drive DDDM.

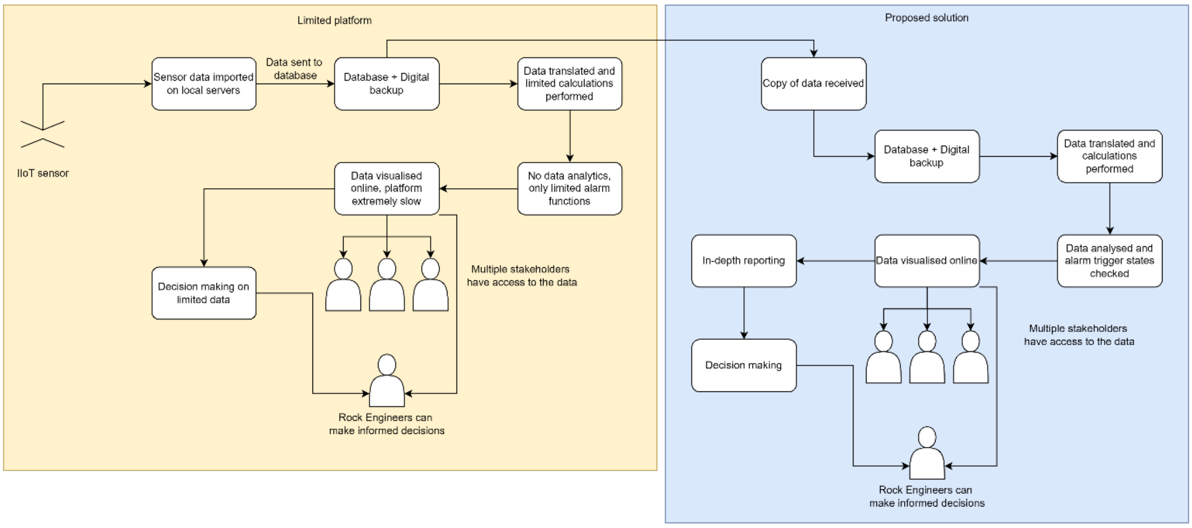

Figure 4. System solution for an inadequate visualisation platform.

AVAILABLE SOLUTIONS

The software used as the solution by Groundwork Consulting to mitigate the difficulties being experienced by the mining company, analysed the data as seen in Figures 9 and 10. From this graph extensive knowledge could be derived, and actual closure events could be recognised, such as blasting events taking place. A holistic view of the location data could be provided. See Figure 5 for the actual data representation.:

Case study 3 – Data analytics

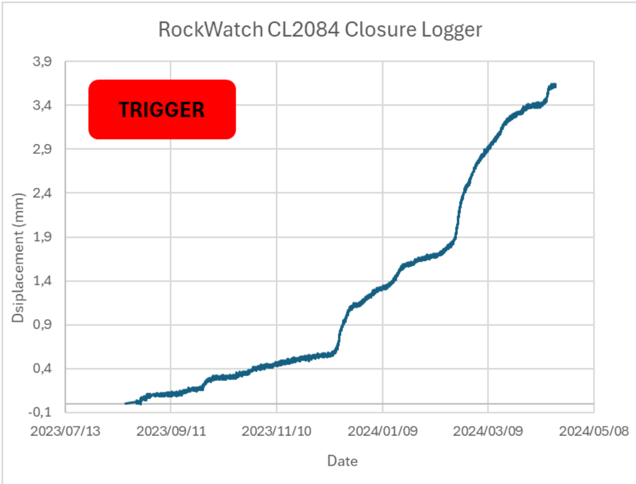

Figure 5. Actual data representation from the proposed solution.

When viewing Figure 5 and looking at studies done on closure in 'Experimental validation of a mine-wide continuous closure monitoring system as a decision making tool for gold mines' (Malan *et al*., 2003), it is clear that an inadequate visualisation platform incorrectly visualises and analyses data, and removes the context of the data. It also distorts the true meaning of the data. No valuable decisions could be made as to the state of the rock mass from the inadequate platform being used which could have serious consequences. From the report 'Experimental validation of a mine-wide continuous closure monitoring system as a decision-making tool for gold mines' (Malan *et al*., 2003), the following insights could be drawn from adequate visualisation of closure data:

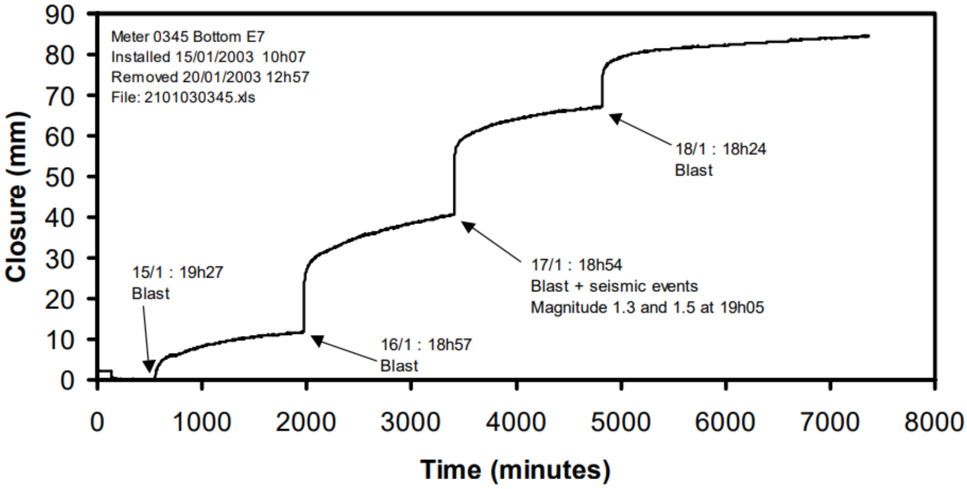

Figure 6. The context behind closure graphs.

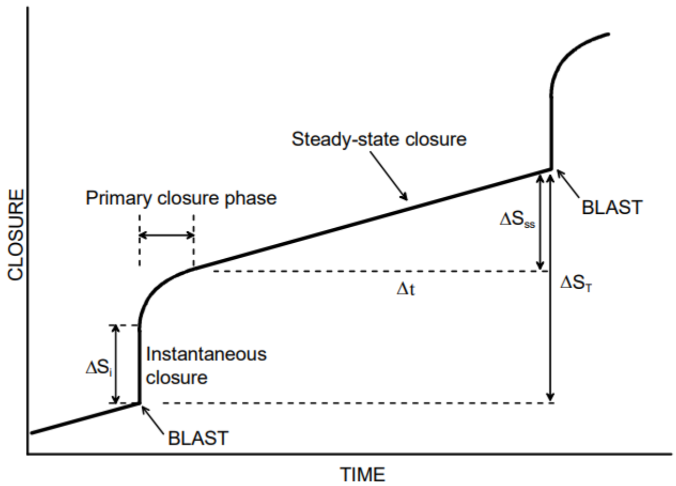

Figure 7. Methods of analysis to be used when applying analytics to closure graphs.

Figures 6 and 7 clearly show that visualisation and analytics need to be properly defined, and that data in its raw format is meaningless when visualised without context and understanding. It is therefore critical for mining companies to understand the data, and to properly visualise and analyse data to promote DDDM. The platform currently used by Groundwork Consulting has numerous other benefits and had the following view for different parameters. The closure profile was visualised in Figure 8.

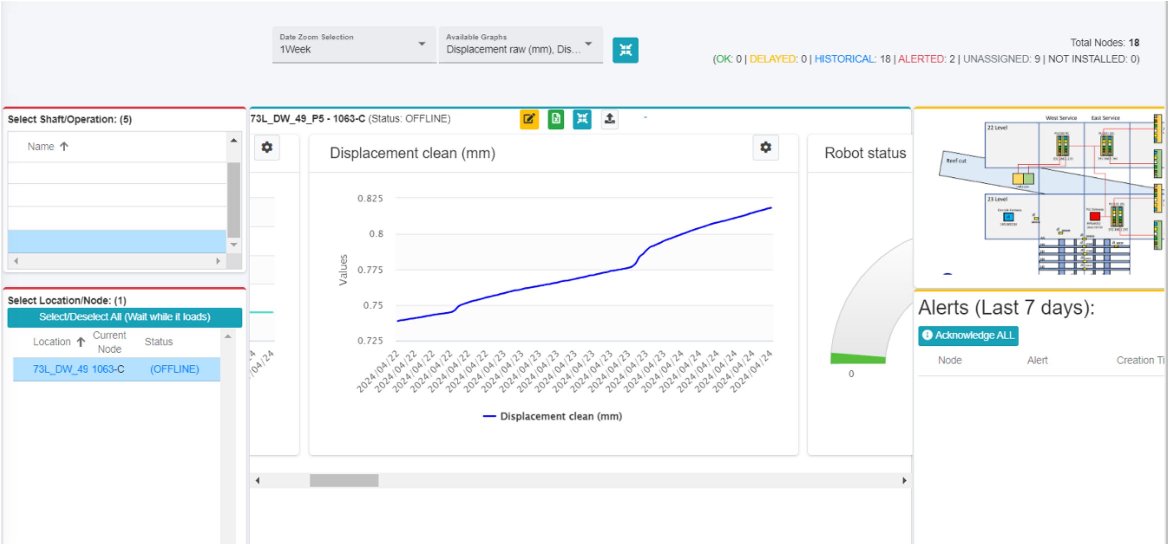

Figure 8. Advanced visualisation and analytics software as proposed solution.

The graph could also be expanded for some additional tools to visualise the data in-depth:

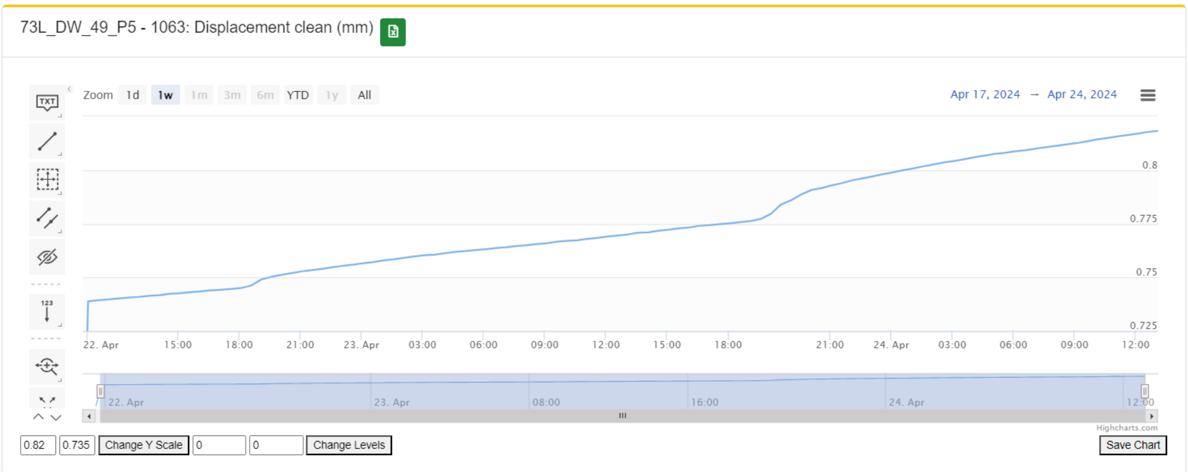

Figure 9. Expanded graphing tools from advanced visualisation and analytics platform.

The platform also included the following graphs based on analytics and holistic data analysis:

1. Robot status charts.
2. X and Y-acceleration graphs.
3. Air temperature graphs.
4. Barometric pressure graphs.
5. Battery voltage charts.
6. Rate-of-change graphs.
7. Inverse velocity graphs.
8. Tilt charts.

CONCLUSION

The field of rock engineering is undergoing a significant transformation driven by the increasing availability of advanced sensors and sophisticated software for real-time monitoring. The integration of the IIoT into rock engineering processes has opened new avenues for data collection and analysis, enabling the generation of actionable insights like never before. This paper underscores the importance of adopting a phased approach to automated data processing and insight generation to manage costs, reduce risks, and optimise resource utilisation. The DIKW and IIoT models are crucial to keep in mind when selecting platforms for DDDM. Throughout the process of selecting, implementing, and evaluating various software solutions for geotechnical applications, several key lessons have emerged. These insights are crucial for rock engineers aiming to transition from manual to automated data management systems and for selecting the most appropriate visualisation platforms. Some key lessons learnt are summarised below:

Phased approach and strategic implementation
Adopting a phased approach to data automation allows rock engineering departments to gradually transition from manual to automated systems, thereby lowering costs and resource requirements. This step-by-step implementation helps mitigate the complexities and high expenses associated with full automation. The phased strategy ensures that each stage of data collection and processing (from sensing to visualisation and analytics) is carefully planned and executed, leading to more accurate and efficient decision-making processes.

Importance of appropriate software selection
Selecting the right software is crucial for effective data management and visualisation. With a plethora of geotechnical software options available, it is essential for rock engineers to understand the specific requirements for their operations and to choose software that meets these needs. Key criteria for selecting suitable software include customisation capabilities, data file format compatibility, data management features, and ease of integration with existing systems.

Moving forward with data analytics
The transition to automated data processing and advanced analytics is not just a technological upgrade but an essential evolution to keep pace with industry standards and improve operational efficiency. By leveraging DS, ML, and AI, rock engineering can move from basic data collection to sophisticated predictive analytics and decision support systems. These technologies help eliminate manual errors, speed up information processing, and provide deeper insights into rock mass behaviour, ultimately enhancing safety and operational performance.

Final recommendations
Rock engineering departments are encouraged to embrace the IIoT model as a foundational step toward automation. Starting with the integration of advanced sensors and robust data management systems, engineers can progressively build towards more complex analytics and decision-making frameworks. The selection of appropriate software packages should be guided by a clear understanding of operational needs, supported by thorough testing and validation. By following the lessons and best practices outlined in this paper, rock engineers can effectively navigate the transition to automated systems, ensuring data integrity, improving decision-making, and maintaining compliance with safety regulations.

In conclusion, the journey towards fully automated monitoring and data-driven decision-making is both challenging and rewarding. By taking a strategic, phased approach and leveraging the right technologies, rock engineering departments can achieve significant improvements in efficiency, safety, and operational effectiveness.

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Jaco is passionate about developing embedded IoT systems and designing automation systems for geotechnical applications to provide holistic overviews, enabling data-driven decision-making.