Advances in integrated performance monitoring of Tailings Storage Facilities

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Abstract

Since the initiation of the Global Industry Standard on Tailings Management (GISTM), the adoption by mining companies of advanced monitoring technologies has expanded. These systems utilize continuous, near-real-time data from diverse sensors, integrating geotechnical, hydrological, and environmental measurements. Enhanced by real-time data fusion and advanced statistical analysis, the technology enables the detection of subtle structural deviations, improving the accuracy of quantitative risk assessments, and reducing false positives. Dynamic, tailored response plans are activated based on detected anomalies and forward-looking statistical trend analysis, enabling swift, informed decision-making. This approach enhances safety and proactive risk management for tailings storage facilities and promotes regulatory compliance, operational efficiency, and sustainability.

Keywords: GISTM, Tailings Management, Advanced Analytics, Sustainability

Introduction

Tailings storage facilities (TSFs) have attracted increasing attention from international investors, insurers and the United Nations due to catastrophic failures, prompting industry changes. One key outcome was the publication of the Global Industry Standard on Tailings Management (GISTM), which emphasizes integrated performance monitoring as a safety measure (GISTM, 2020). Guidelines for TSF monitoring have been established, promoting best practices and effective oversight (Zare *et al.*, 2024). As a result, new monitoring technologies have emerged, including:

- Real-time sensor data collection
- Data integration and management in the cloud
- Real-time statistical analysis
- Anomaly detection
- Machine Learning and AI

These innovations offer benefits like reducing false positives, improving risk assessments, speeding decision-making, automating response plans, enhancing disaster preparedness, reducing compliance efforts, and cutting operational costs. This paper focuses on the value of these technologies for safety, monitoring, proactive risk management, and automated responses.

Monitoring Techniques for Tailings Storage Facilities

Before the widespread availability of sensors and Internet of Things (IoT) devices enabling automated monitoring, visual assessments and manual measurements were the primary tools used in surveillance monitoring. These processes were manual and time consuming, resource-intensive, and introduced the possibility of human error. The clear need for implementation of more effective monitoring systems, coupled with the affordability and scalability of IoT-enabled sensor networks, has propelled the industry toward digitized and automated data collection.

A systematic review by Cacciuttolo *et al.* (2024) analyzed 52 studies from Web of

Science (WoS) and Scopus databases, highlighting the widespread use of modern technologies. 90% of the papers analysed specified the use of real-time automatic measurements.

These new advanced monitoring technologies create the potential for a greater understanding of critical failure mechanisms, or modes, enable early detection of potential triggers, and support tailings dam design and expansion. By integrating these systems, the industry can transition from reactive to proactive risk management, ensuring safer and more efficient operations.

Automated Data Processing

The typical monitoring data flow from TSF instrumentation is **collection**, **transformation**, **validation**, **processing**, and **visualisation** (Insight Terra, n.d.). Automated data collection from TSF instrumentation begins with data collection through local wireless gateways and networks. This data at site level is normalized, and compressed, ensuring efficient and secure transmission to the cloud via either terrestrial or satellite connectivity. Upon reaching the cloud, each raw measurement enters a real-time data pipeline and undergoes validation and transformation against predefined accuracy thresholds before processing.

Following validation, the data is enriched with installation details and other relevant metadata to produce contextualised data with the correct engineering units. Raw data persists, whilst the calculated engineering metrics progress to the next step of real-time analysis by logic algorithms, which are designed to extract contextual information, generate insights, identify anomalies, and trigger alerts when predefined thresholds are exceeded. The processing and analysis of each metric in real-time differ substantially from retrospective analysis. Analysing the data quality through each step reduces the potential for false positives. Invalid data is stored separately from valid data for further analysis. Finally, the processed data is made available to other systems and visualisation tools, allowing users to create dashboards and use the data for informed decision-making and processes like root cause analysis.

Advanced Data Processing and Analysis

Historically, each retrieved parameter would be evaluated individually to determine any structural changes in the TSF. However, more recently multi-dimensional data sources are being integrated into a single framework for improved analysis. As demonstrated by Mwanza *et al.* (2024), the combination of geotechnical, environmental, and hydrological parameters through digital twin simulation and machine learning enables a more comprehensive analysis of TSF stability. This integration allows for real-time monitoring as well as predictive insights that weren't possible with traditional single-parameter assessments.

Unified data frameworks derive new insights via advanced analytics. As the proliferation of IoT sensors and instrumentation broadens data availability, previously unrecognized correlations among parameters become apparent. This evolution is demonstrated in contemporary TSF monitoring methodologies, where enhancements in real-time data acquisition, coupled with machine learning (ML), are significantly advancing failure prediction capabilities. By integrating digital twin technology and ML algorithms, TSF management is transitioning from straightforward parameter monitoring to sophisticated predictive analytics. This allows the detection of early warning signs across various failure modes, thereby enabling more proactive risk management and strengthening safety measures. This represents a substantial progression from traditional monitoring techniques, which primarily depended on explicit mathematical correlations among single parameters.

Fig. 1 on the next page depicts the processing steps of a single payload of data containing measurement metrics from a geotechnical instrument with several data points, such as an inclinometer.

The received data payload, which includes multiple metric measurements (e.g., from a MEMS inclinometer), undergoes the following processing steps:

1. Quality assurance: Each metric within a data point is initially checked to ensure accuracy and reliability.

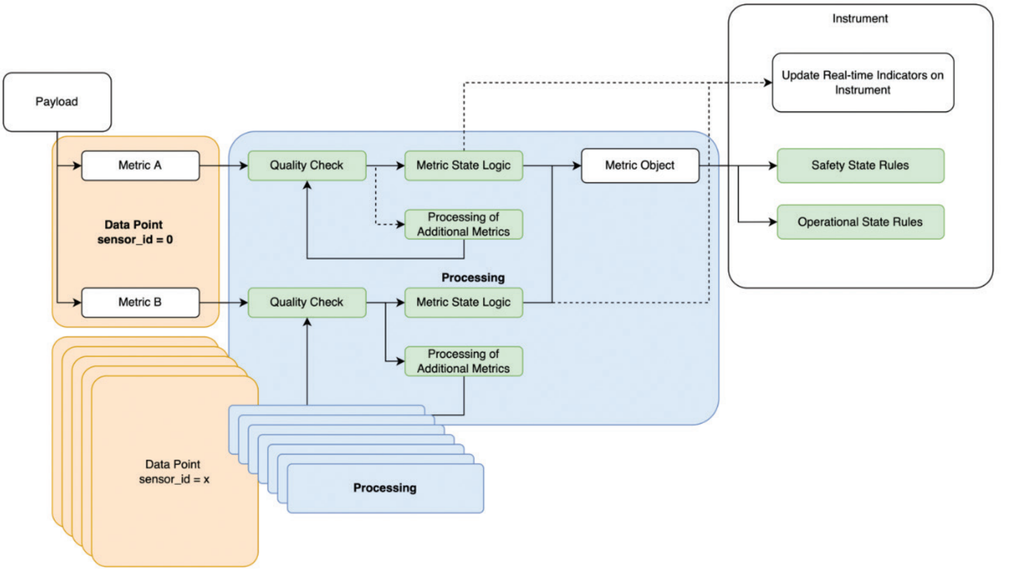

Figure 1 *Data Processing Step for a Payload.*

2. Metric state analysis: After quality assurance, each metric is subjected to state logic analysis for detecting abnormalities and trends. This analysis also updates the real-time indicators of the instrument.
3. Extended metric processing: Further metrics are generated for each data point using a processing script. This includes querying historical data, enhancing the depth of analysis, and conducting additional logical validations.
4. Data persistence and rule application: After processing, metrics are stored and subsequently integrated into a rules engine. This engine activates safety and operational state protocols.
5. Complex scenario execution: The safety and operational states execute comprehensive analyses across all metrics and data points, determining the appropriate indicators for monitoring system integrity and operational safety.
6. Virtual device handoff: The payload may also be transferred to virtual devices for additional processing. These virtual devices handle multiple payloads from various instruments, each running through its own designated processing script and generating a new set of metrics.
7. Nested entity triggering: Any nested monitoring entities are triggered for processing once the initial instrument entity completes its safety and operational state processing.
8. Data point group invocation: Groups of data points can be created from new payloads from one or more similar instruments, to undergo the same process, including safety and operational state processing.

Micro Trend Analysis

Geotechnical instrumentation metrics are implicitly slow to change. They require long-term analysis to identify macro trends. However, by the time these trends become clear, addressing their impact may be costly and disruptive. Real-time analysis, enabled by the availability of real-time data, can be implemented to detect micro trends in time-series data. A trend change can serve as an early warning for large incidents.

Statistical Process Control (SPC) approaches can track data fluctuations and identify anomalies that may signal abnormal conditions in the tailings structure. These methods detect potential dangers by analysing characteristics such as tailings density, settlement rates, and groundwater levels (Harvey, 2023). More particularly, the Nelson Rules, first introduced in Lloyd S. Nelson's publication The Shewhart Control

Chart: Tests for Special Causes (Nelson, 1984), provide a formal framework for finding exceptional causes of variation in a process through microtrend analysis. The Nelson Rules can be used inside SPC to discover early warning signs of impending problems. This allows stakeholders to be proactive in maintaining the safety of tailings facilities.

Limited research has been published on the application of these rules in the mining industry. Other industries have however successfully implemented these practices. The paper, "*Condition Monitoring of Internal Combustion Engines in Thermal Power Plants Based on Control Charts and Adapted Nelson Rules*" (Vilas Boas *et al.*, 2021), is an example of a successful application of Nelson Rules. Their findings highlight how SPC and Nelson Rules can be used for early failure detection, predictive maintenance, and decision-making to prevent costly breakdowns. It is reasonable to conclude that this process is similarly useful for tailings management.

How these rules can apply to tailings management is discussed next, focusing on Rules 1 to 4 due to their relevance to sensor performance and geotechnical stability.

1. Extreme Deviation (One point is more than 3 standard deviations from the mean)
   a. Geotechnical Implications: This may indicate sudden instability, such as excessive pore pressure.
   b. Sensor Implications: Possible sensor malfunction.
2. Prolonged Bias (9+ consecutive points on one side of the mean)
   a. Geotechnical Implications: Suggests a new norm has been reached, requiring a recalculation of the mean.
   b. Sensor Implications: Could indicate sensor drift
3. rending Data (6+ consecutive points increasing or decreasing)
   a. Geotechnical Implications: Reflects progressive changes such as soil consolidation, tailings compaction, or embankment settlement.
4. Oscillations (14+ points alternating in direction)
   a. Geotechnical Implications: Unlikely to be caused by natural factors
   b. Sensor Implications: This likely points to a faulty sensor.

In addition to the Nelson Rules, various statistical techniques can be used to analyse trends and determine TSF stability. Comparative stability analysis methods, such as those described in "Comparative Stability Analysis of Tailings Storage Facilities" (Vega Vergiagara *et al.*, 2021), offer alternate means of monitoring TSF behaviour. Raw data can be turned into useful information about the sensor network and TSF stability by using various statistical methodologies.

To aid in proactive decision-making, an automated notification system can be built to alert stakeholders when anomalies are identified. These notifications then connect stakeholders to a dashboard that shows key performance indicators (KPIs) relating to TSF conditions. Such dashboards enable engineers and decision-makers to monitor trends, identify abnormalities, and take proactive measures. By leveraging real-time analytics and SPC techniques, TSF management can become more proactive, reducing the risk of major incidents and ensuring long-term stability.

Creating and Enhancing Response Plans

Trigger Action Response Plans (TARPs) can be employed to systematically manage risks in TSFs by defining clear actions based on predefined safety or operational thresholds. Integrating TARPs with real-time data is essential for enhancing the safety and efficiency of TSFs. As highlighted by Nunes *et al.* (2023), TARPs are designed to address deviations from normal operating conditions through a tiered response system, ensuring timely interventions that reduce the likelihood of structural failures and restore safe conditions.

The Response Plan Data Model in Fig. 2 ensures a structured approach to risk management by linking safety states, responder types, monitoring entities, and supporting documentation. Each response plan is linked to an Operational/Safety State Indicator, defining risk levels, categorized by colour levels (e.g., Red for critical conditions). It is assigned to a Responder Type, which mimics a persona, e.g. Engineer of Record (EOR) or Responsible Tailings Facility Engineer (RTFE). This ensures that correct actions are taken by the appropriate individuals. Monitoring entities, including sensors, interface nodes, physical and virtual devices, and data point groups, visualise their safety or operational states (Red, Orange, Yellow, Blue, Green) in real-time based on the predefined trigger conditions. Monitoring entities activate response plans when they detect a specific state. Furthermore, attachments such as procedural documents and schematics are linked to response plans, guiding responders.

Fig. 3 illustrates how the above data model is used for Monitoring Entity A. If Monitoring Entity A triggers a RED safety state, all the relevant responders (in this case Responder A and B) will be allocated their respective RED response plans. If the safety state were to later change to YELLOW, different responders (e.g. Responders B and C) would be assigned their associated YELLOW response plans. The same goes for the ORANGE, BLUE, and GREEN states. Email notifications and monitoring applications ensure that the appropriate details are conveyed to the designated responders in real-time.

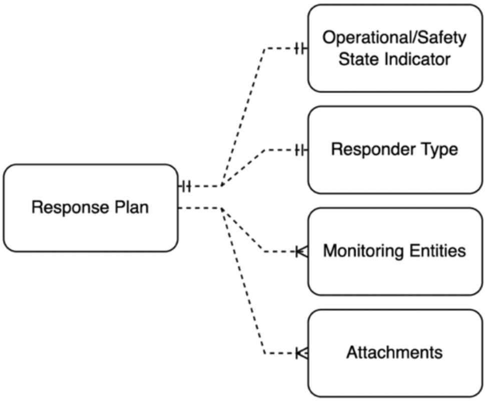

Figure 2 *Response Plan Data Model.*

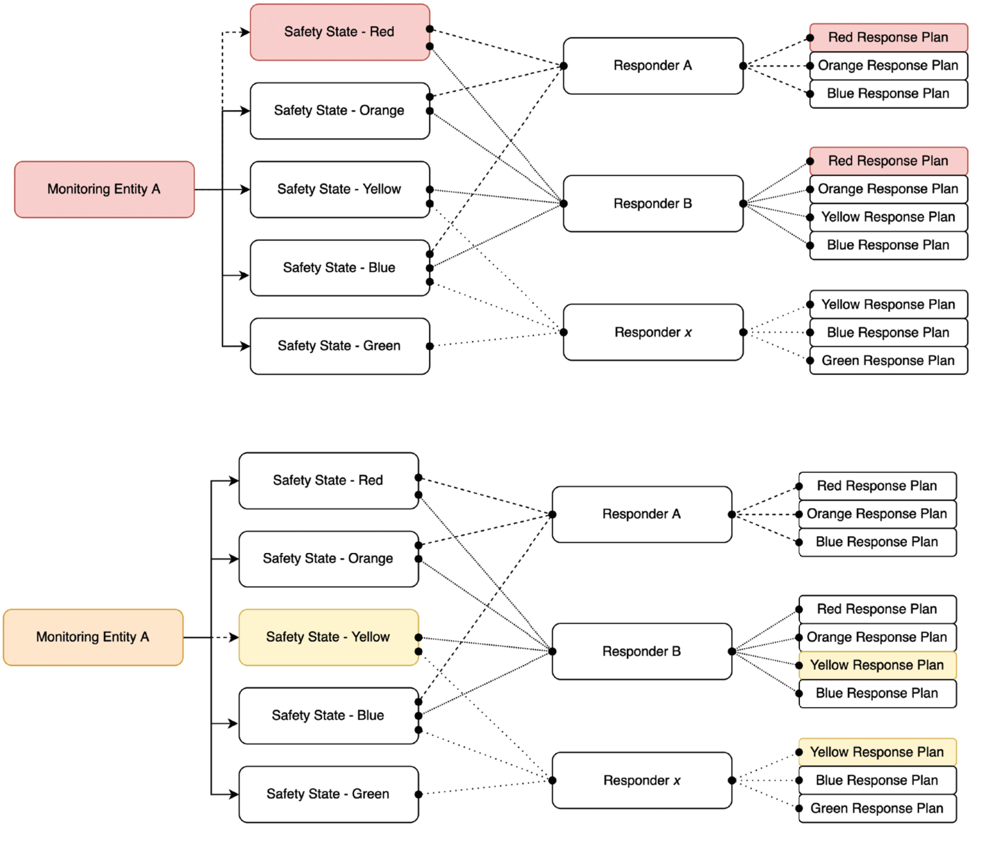

Figure 3 *Trigger Action Response Plan Example.*

Applications, Broader Implications, and Industry Transformation

The adoption of advanced monitoring technologies in TSFs is reshaping industry practices, enhancing safety, sustainability, and operational efficiency. The industry is making steady progress in integrating these technologies, particularly following the implementation of the GISTM.

Despite the clear benefits of these advancements, challenges remain regarding widespread adoption across all facilities, particularly among smaller operators facing budget constraints. Nonetheless, the industry's commitment to improving safety standards through technology is evident as it progresses towards more sustainable and efficient TSF management solutions.

The future of TSF management lies in the implementation of advanced technologies such as automated instrumentation, AI, and digital twins. Digital twins, which create virtual replicas of physical systems, offer predictive insights and enhance monitoring capabilities. The integration of ML/AI and IoT technologies into mining automation presents opportunities for improved data security, transparency, and operational efficiency (Cacciuttolo 2024).

Conclusions

Advancements in integrated monitoring of TSFs have transformed risk management into a proactive process. By leveraging near real-time data, advanced SPC, and automated response plans, the industry can detect anomalies earlier, reduce false positives, and implement dynamic mitigation strategies. The implementation of multi-dimensional data analysis and ML/AI-driven insights that are integrated into the overall surveillance and performance monitoring processes enhances TSF safety and optimizes response planning, ensuring compliance with evolving industry standards such as the GISTM. Beyond safety improvements, these innovations offer cost savings, environmental benefits, and operational efficiencies that drive broader industry transformation. As technology advances, the incorporation of predictive analytics, ML/AI, and digital twin modelling will further refine TSF management practices, paving the way for a safer, more sustainable future in the mining sector.

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