WHITE PAPER

ARTIFICIAL INTELLIGENCE-DRIVEN MINE DEWATERING TO IMPROVE SAFETY AND EFFICIENCY

Abstract

Water accumulation in mines poses risks like flooding and hazardous in-rushes, compromising infrastructure and safety. Effective mine dewatering is essential for operational safety and efficiency, requiring continuous pumping to manage groundwater inflow. Traditional prediction methods, such as empirical equations and finite-element models, face limitations due to geological and hydrological complexities.

This paper describes an Artificial Intelligence (AI) based monitoring approach as a soft sensor for mine dewatering systems. Utilizing sensors to track water levels, flow rates, and pump power consumption, real-time data is fed into an AI/Machine Learning (ML) model to detect anomalies and predict potential issues. The system employs Principal Component Analysis (PCA) for anomaly detection, focusing on static window PCA due to its simplicity and effectiveness in stationary environments.

Alerts for abnormal behaviors, such as pump failures or excessive groundwater inflow, provide early warnings to maintenance personnel. An additional monitoring system enhances these alerts with specific parameter checks, including water flow, pump current anomalies, and groundwater inflow. These empirical rules improve the interpretability and actionability of alerts.

This AI-based soft alerting system has been implemented in a large mining operation. It has demonstrated its potential to enhance the efficiency, safety, and cost-effectiveness of mine dewatering processes. Continuous monitoring and feedback loops ensure the system adapts to operational needs, offering a robust solution for mine water management.

INTRODUCTION

The accumulation of water in mines can cause issues to the integrity of various mine infrastructures when excessive quantities of water combine with other materials, potentially resulting in dangerous in-rushes (Runs of Muck). A fundamental problem is the clogging of ore or waste passages formed because of excessive uncontrolled water in the active mining heading areas.

Mining operations are also prone to flooding, a significant disaster that shuts down operations with costly repercussions and triggers Environmental Health and Safety (EHS) issues. Groundwater can infiltrate the working area when a mine extends below the water table. This is accelerated by heavy rainfall and drainage from backfill and nearby rivers and lakes. The constant influx should be continuously pumped out to prevent flooding.

Thus, proper dewatering is essential for

Ensuring the safety of mining operations. Excess water in mines can lead to hazardous conditions, such as flooding, which can halt operations and endanger workers.

Maintaining dry conditions in the mine improves operational efficiency and equipment lifespan by reducing the wear and tear caused by water.

The dewatering system comprises of a set of pumping systems with high head capabilities and high kilowatts of power positioned at multiple levels to help raise the water and debris from the bottom of the pit. It may also involve additional booster pumps to overcome the larger vertical lift, especially when mining operations are at a greater depth.

The mine dewatering requires continuous monitoring for anomalies that could occur due to environmental conditions, problems with the dewatering system components or other possible causes. Hence, monitoring is critical for uninterrupted and safe underground mine operations. Moreover, early detection of anomalies can help maintenance personnel take necessary precautions to avoid mine interruptions and safety issues. Typical anomalies include:

Excess inflow of groundwater, leading to overload of the current dewatering system.

Failure in any dewatering system components, such as pump failures, etc., leads to ineffective mine dewatering.

Monitoring the operating conditions and the dewatering system enables early prediction of anomalies and the necessary remedial measures.

There are few published approaches related to predicting anomalies in a dewatering system. Fawcett et al. [1] published empirical equations and analytical solutions to predict dewatering requirements. This approach is complex and involves many uncertainties in accurately predicting water inflows due to the heterogeneous nature of geological formations and the variability in hydrological conditions. The models often rely on assumptions and simplifications that may not fully capture the real-world complexities, leading to potential inaccuracies in the predictions. Larry et al. [2] used a 2D finite-element model representing a geologic section across the deposit to understand the time-variant de-watering requirements for a mine. This methodology has challenges in accurately representing complex geological and hydrogeological conditions. This complexity, coupled with the need for extensive field data and extended model boundaries, can lead to uncertainties that affect the model's accuracy.

This paper describes an AI-based monitoring approach in which the mine dewatering system has various sensors to monitor different aspects such as reservoir water levels, quantity of water flown and pump power consumption. The aim is to utilize the available sensor data information and develop an AI/ML-based anomaly detection model that could highlight abnormalities in the mine dewatering system, indicating deviations from normal operations. This helps monitor and investigate such issues in advance so that proper preventive actions can be taken proactively.

OVERVIEW OF MINE DEWATERING SYSTEM

The mine dewatering system involves multiple pumps, storage units, settling ponds, and a surge bin, all monitored by sensors that provide real-time data. Figure 1 Outlines a high-level overview of a dewatering system for a mine that integrates an AI-based monitoring system for anomaly detection.

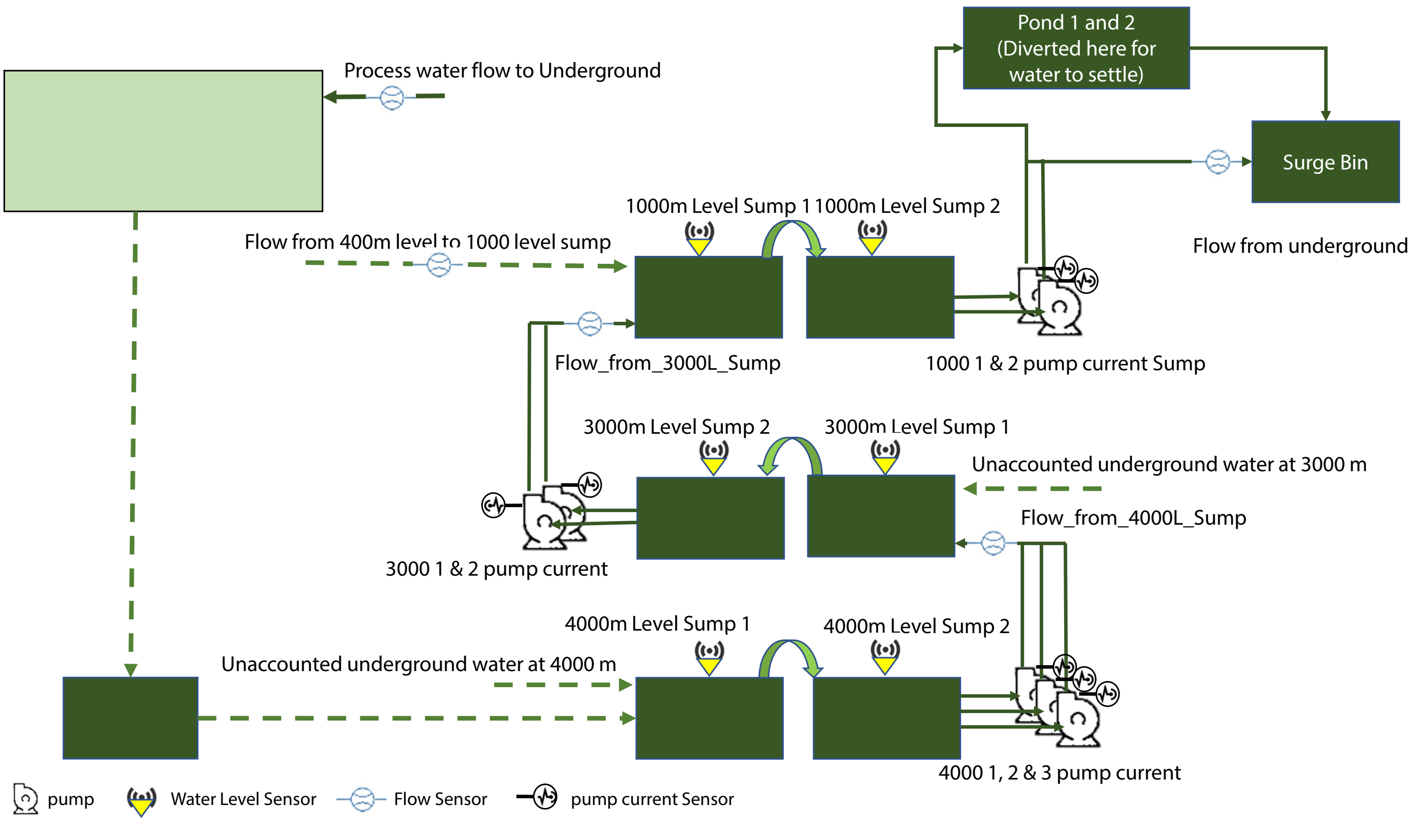

Figure 1: Mine Dewatering System Overview

The foundational component of the mine dewatering system consists of the physical infrastructure responsible for removing water from the mine. There are sumps that collect water at different levels below the ground. Inflow water to the mine at various levels is channeled to the sumps at that level. Multiple pumps move water from sumps at the lower level to the ones at the higher level. At the ground level, the final lifted water is temporarily stored in few ponds to allow sediments to settle before being pushed to the surge bin.

Mine Water Inflow:

Mine inflow water enters the system through the entry point indicated by the red arrow.

Storage Units / Sumps:

These represent storage units or tanks where water is temporarily held before being pumped out or further processed.

Pumps and Pipelines: Various levels of mines in the system represent pumps that move water through different stages of the dewatering process:

- o Three (4000 – 1,2,3 pumps) pump the water from 4000 m below ground to 3000 m.
- o Two (3000 – 1,2 pumps) pump the water from 3000 m below ground to 1000 m.
- o Two (1000 – 1,2 pumps) pump the water from 1000 m below ground to ponds 1 and 2, the settling ponds to subsequent stages.

Water Ponds:

Water is diverted to Pond 1 and Pond 2 for settling. These ponds allow the sediments to settle before the water is further processed.

Surge Bin:

The surge bin receives water from the pumps and serves as an intermediary storage before final disposal or treatment.

Additionally, various sensors have been incorporated to collect the required data. It includes the following:

Water Level Sensors: These sensors track the water levels in different sumps of the dewatering system, ensuring that water is being effectively removed and managed. Each storage unit is equipped with level sensors to monitor the water level.

Water Flow Sensors: These sensors monitor the flow rate and volume of water moving through the system at different locations, i.e., entry or exit of the sumps. These sensors provide real-time data to ensure efficient operation and detect anomalies by tracking water movement throughout the system, allowing for precise control and anomaly detection.

Pump Electrical Current Sensors: These sensors monitor the electrical current consumed by the pumps, providing insights into their operational status and efficiency. The electric current consumed is recorded in real-time to ensure efficient monitoring of operation and load on the pumps. Each pump is equipped with an electric current sensor.

Data from the water flow, pump current, and water level sensors is continuously collected. This data provides real-time information about the operational status and performance of the dewatering system and is fed into an AI-based monitoring system.

AI-BASED MONITORING OF MINE DEWATERING

Monitoring the mine dewatering is critical for continual and safe underground mine operations. Continuous monitoring is required to help detect potential anomalies early. AI/ML algorithms can analyze this data to optimize operations, predict potential issues and ensure an alert about flooding of mines. The objective is to utilize the available sensor data information and develop an AI/ML-based anomaly detection model that could highlight the abnormalities in the mine dewatering system, indicating deviations from normal operations, and thereby help monitor and investigate such issues proactively to trigger timely actions.

The primary output of the AI-based monitoring system outlined in Figure 2 is to predict anomalies based on real-time data from various sensors embedded in the mine dewatering system. When an anomaly is detected, the system triggers alerts or takes predefined actions to address the issue. This proactive monitoring helps maintain the efficiency and effectiveness of the dewatering system, preventing potential downtime or damage.

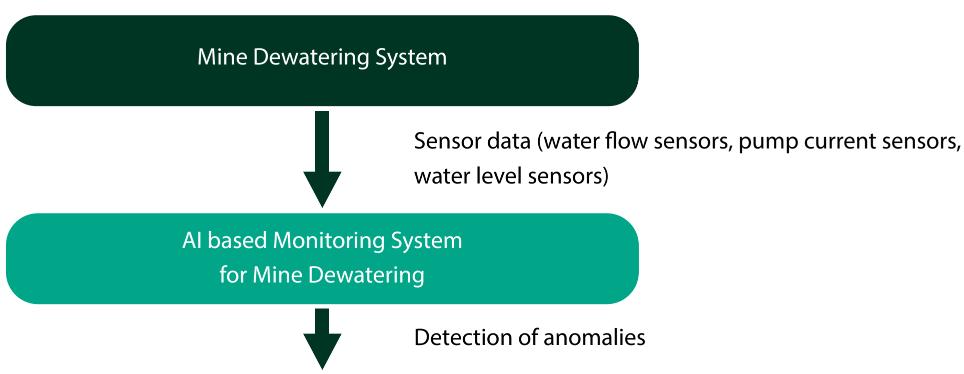

Figure 2: AI-based Monitoring system for Mine Dewatering

An AI/ML-based monitoring system for mine dewatering offers several advantages over traditional systems:

Predictive Analytics:

AI/ML systems can analyze historical data to accurately predict future water inflows and dewatering requirements. This helps in proactive management and reduces the risk of unexpected flooding.

Scalability and Flexibility:

These systems are scalable and can easily adapt to different mining environments and changing operational requirements. This flexibility makes them suitable for a wide range of mining operations.

Real-Time Monitoring and Adaptive Control:

These systems can continuously monitor various parameters in real-time and adapt to changing conditions dynamically. This ensures optimal performance and efficient resource utilization.

Anomaly Detection:

Advanced ML algorithms can detect anomalies and potential issues early on, allowing for timely interventions and reducing the likelihood of operational disruptions.

Data Integration and Comprehensive Analysis:

AI/ML systems can integrate data from multiple sources (e.g., sensors, geological surveys, weather forecasts) and provide a holistic view of the mine's water management. This leads to informed decision-making.

Thus, AI/ML-based monitoring systems for mine dewatering provide superior predictive capabilities, real-time monitoring, and adaptive control, leading to enhanced efficiency, safety, and cost savings compared to traditional dewatering systems.

SOLUTION APPROACH FOR AI-BASED MONITORING

The AI-based mine dewater monitoring solution approach comprises an advanced algorithm that analyzes the data using machine learning techniques. The AI system processes and analyzes the sensor data to identify patterns and trends. It learns the normal operating conditions of the dewatering system. By comparing real-time data against learned patterns, the AI system can detect deviations that may indicate potential issues or anomalies. These anomalies could indicate problems such as pump malfunctions, blockages or unexpected water inflow.

This solution has been implemented using Principal Component Analysis (PCA), a dimensionality reduction and ML method that reduces a large data set into smaller data set while maintaining significant patterns and trends in the original data set.

Various approaches and methods of implementing the PCA technique for anomaly detection, viz., the Static window PCA and the Moving Window PCA technique [3], have been analyzed in detail.

Static Window PCA Technique

This method involves analyzing data within a fixed, pre-defined time window to identify deviations from normal patterns (Figure 3). This method has two phases of implementation: an offline or training phase is used to construct and validate the PCA model, while the online phase is used to monitor the new testing samples. Any violation of the threshold set based on the training phase would indicate that an unusual event has occurred, causing a change in the covariance structure of the model. Based on the previous description, the abnormality is indicated if Q or T2 statistics exceed their confidence limits.

Figure 3: Static PCA: Training & Test Window

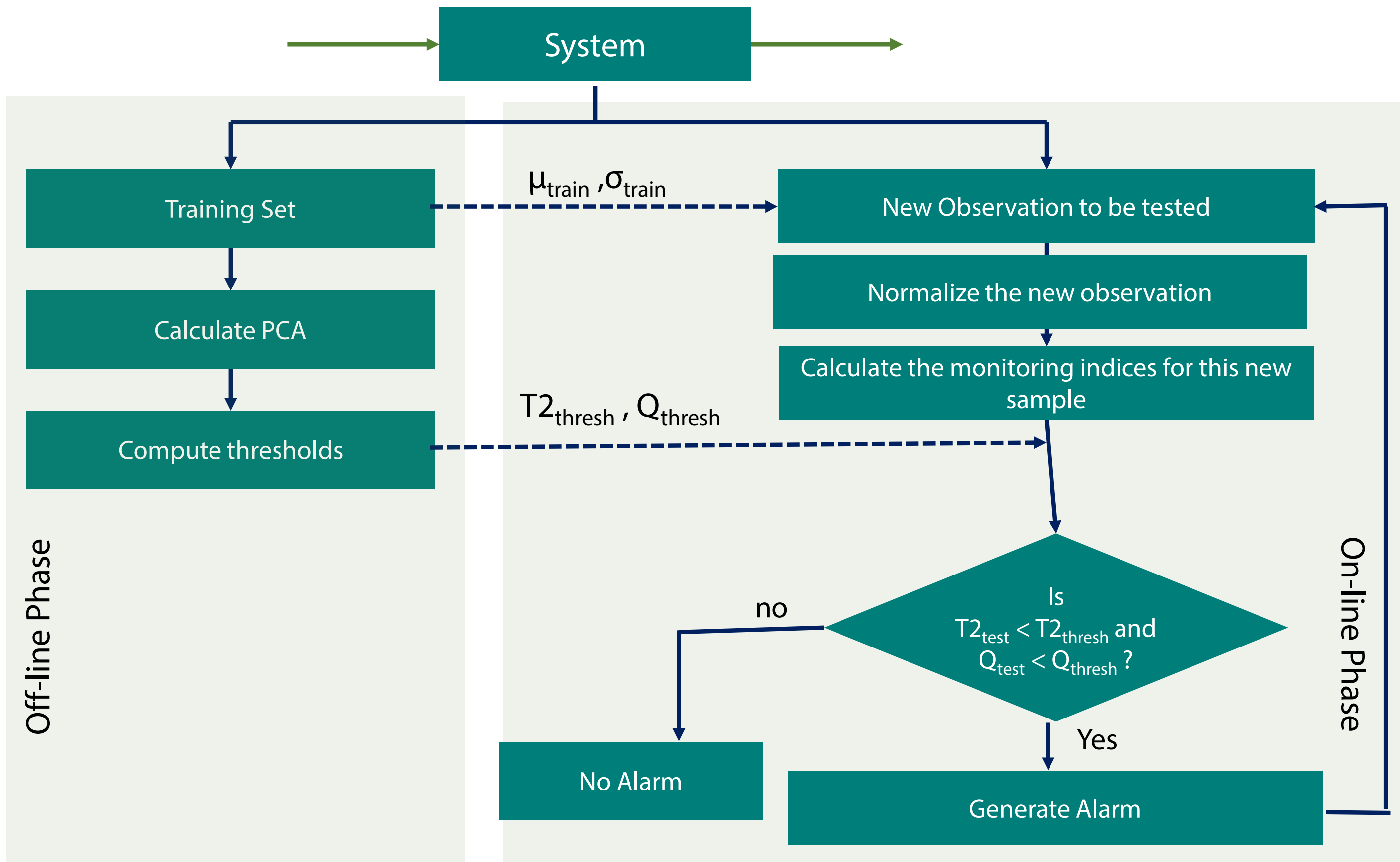

Figure 4: Static Window PCA Approach

The flow diagram for this approach is shown in Figure 4. Some of the advantages and limitations of the static PCA technique are:

Advantages

Simplicity: It is relatively straightforward and does not require complex computations.

Effectiveness: It can effectively capture and model normal behavior in systems with stationary processes.

Dimensionality Reduction: It reduces the data complexity by focusing on the most significant variance features, making it easier to detect anomalies.

Limitations

Fixed Window Size

The static window size must be chosen carefully. If the window is too large, it may dilute anomalies; if it is too small, it may miss broader trends.

Stationary Assumption

It assumes that the system's normal behavior is stationary within the window, which may not be valid in dynamic environments.

Sensitivity to Parameter Choice

The number of principal components used for reconstruction and the threshold for residuals significantly affect anomaly detection performance.

Moving Window PCA (MWPCA) Technique

The MWPCA method can tackle some of the limitations of static window PCA by collecting enough data points in the time window, which can help build an adaptive process. Specifically, MWPCA removes older samples to choose the new ones representing the current operation process. Hence, for window size K, the data matrix at time k is $x_k=(x_{k-K+1}, x_{k-K+2}, x_{k-K+3},\ldots x_k)$ and, at time k+1, it is $x_{k+1} = (x_{k-K+2}, x_{k-K+3}, x_{k-K+4},\ldots x_{k+1})$. Figure 5 illustrates this.

Figure 5: Moving Window PCA: Training and Testing Window

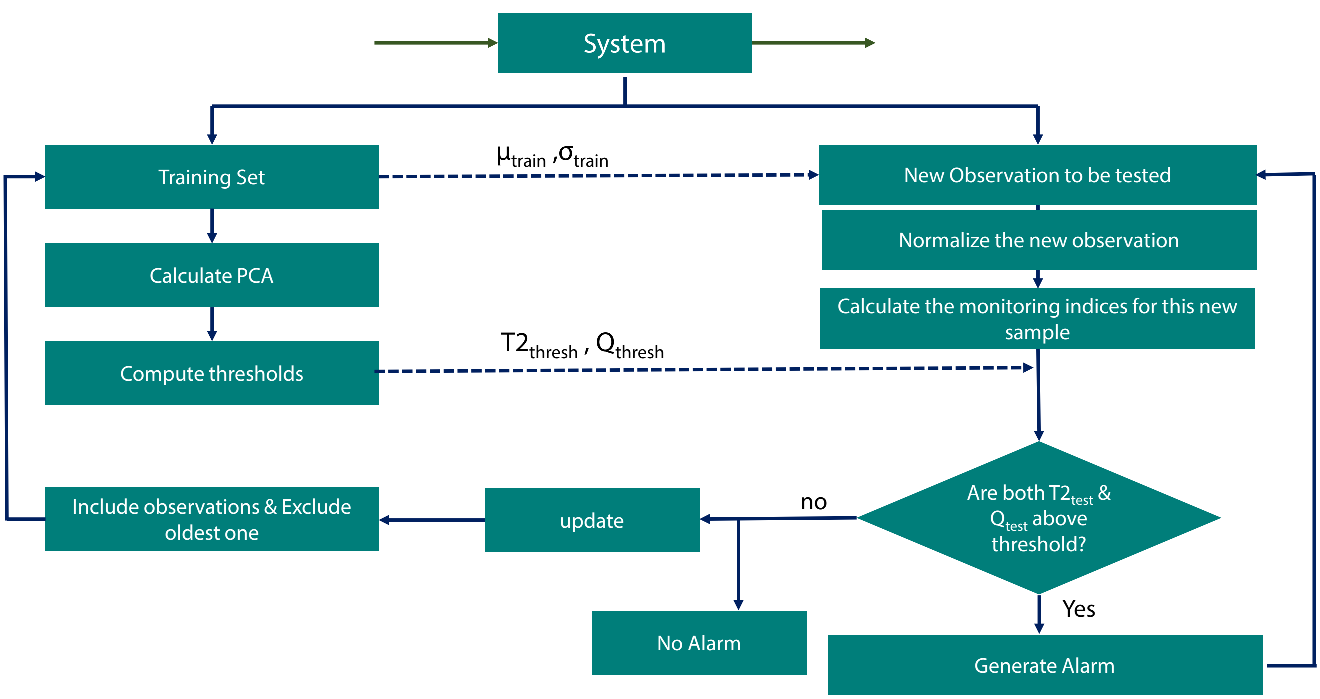

Figure 6: Moving Window PCA Approach

Figure 6 shows the flow diagram for this approach. Some of the advantages and limitations of Moving Window PCA technique are given below:

Advantages

Adaptability to Time-Varying Data: MWPCA can adapt to changes in the underlying patterns of time-series data because it applies PCA iteratively over sliding windows. This allows it to capture evolving behaviors and adjust its anomaly detection thresholds accordingly.

Reduction of Computational Complexity: Compared to batch PCA methods applied over the entire dataset, MWPCA can reduce computational complexity by processing smaller, overlapping data segments. This makes it more feasible to apply to large-scale datasets.

Localized Anomaly Detection: By analyzing data within sliding windows, MWPCA can detect anomalies that occur within specific time intervals. This localization helps pinpoint when anomalies arise rather than just identifying their presence.

Real-Time Monitoring: MWPCA operates in near real-time as it processes incoming data continuously. This capability is crucial for applications where timely anomaly detection is essential, such as monitoring industrial processes or network traffic.

Disadvantages

Parameter Sensitivity: MWPCA performance can be sensitive to window size and overlap parameters. Selecting appropriate parameters requires domain knowledge and experimentation to balance capturing enough variability and ensuring timely anomaly detection.

Windowing Effects: Window size and overlap choice can influence detection sensitivity. Small windows may miss long-term anomalies, while large windows may smooth out short-term anomalies. Finding the optimal window configuration can be challenging.

Cumulative Error Propagation: Errors in PCA reconstruction can accumulate over time, especially if anomalies persist or the underlying data distribution shifts significantly. If not managed properly, this can lead to false alarms or missed detections.

Complexity of Implementation: Implementing MWPCA requires careful handling of data segmentation, PCA computation and anomaly thresholding. Ensuring robustness against different anomalies and data distributions may require additional preprocessing or post-processing steps.

Since the characteristics of mine dewatering system is more static in nature, i.e., the behavior or pattern does not vary with respect to time, hence, the static PCA technique is appropriate for this use case. In addition, the static PCA technique is simple to implement and has faster execution. Based on this analysis, the static window PCA approach was implemented.

This PCA technique generates an alert by detecting the abnormal behavior in mine dewatering for anomalies that could occur due to environmental conditions or problems with the dewatering system components (like pumps or piping system, etc.) or any other causes. However, based on this alert alone, it is hard for the maintenance personnel to troubleshoot and identify the root cause of the abnormal behavior. An additional monitoring engine has been developed to address this challenge, which monitors all system parameters of the mine's dewatering system. The following section elaborates on this.

SYSTEM PARAMETER MONITORING ENGINE

The objective of an additional monitoring engine is to augment the main alert with additional alerts to enable maintenance personnel to investigate issues faster. This monitoring engine monitors all the system parameters of the mine dewatering system individually. Additional alerts are generated corresponding to each parameter in case anomalies are detected with respect to these parameters being monitored.

Based on the physical understanding of the system and data behavior, some empirical rules are developed, and additional alerts are generated to complement the alert based on the PCA model alone. These alerts are indicated to the user in the ML Interpretation section to help them understand specific conditions behind a certain alert.

The following five additional alerts are generated by the system parameter monitoring system.

1. High flow Alert

The high water outflow from 1000L, 3000L and 4000L pumps is calculated based on the formula.

highLimit = (14D Average of Water Flow) * $\left(\frac{125}{100}\right)$

An alert is triggered when '14*day avg of total water flow'* is higher than the *'highLimit'*

Based on historical data analysis, the 'High Limit Threshold' limit is 125%.

2. Low Flow Alert

The low water flow from 1000L, 3000L and 4000L pumps is calculated based on the formula.

lowLimit = ('14D Average of Water Flow^') * $\left(\frac{95}{100}\right)$

An alert is triggered when '14*day avg of total water flow'* is less than the *'lowLimit'*

Based on historical data analysis, the 'Low Limit Threshold' limit is 95%.

3. High full load pump current Alert

Pump overloading typically happens when the motor draws more current than its rated full load. This overloading of the pumps may be due to Misalignment between pump and driver, worn or damaged bearings, or, most of the time, the presence of a slug in a liquid of higher viscosity or blocked intake or discharge.

MeanPumpCurrent = (14D Average pumpcurrent,excluding value below 10amps)

StdPumpCurrent = (14D standard deviation pumpcurrent,excluding value below 10amps)

An alert is triggered when a *days mean current,*excluding the value below 10amps is greater than MeanPumpCurrent+3*StdPumpCurrent

This is calculated for all the pumps located at 1000L, 3000L and 4000L levels.

4. Low full load pump current Alert

Pump underloading typically occurs when the motor draws much less current than the rated full load. This underloading may occur when the discharge line is disconnected or there is a loss of head pressure.

MeanPumpCurrent = (14D Average pumpcurrent,excluding value below 10amps)

StdPumpCurrent = (14D standard deviation pumpcurrent,excluding value below 10amps)

An alert is triggered when a *days mean current*, excluding the value below 10amps is less than MeanPumpCurrent-3*StdPumpCurrent

This is calculated for all the pumps located at 1000L, 3000L and 4000L levels.

5. High Ground Water Alarm

An alert is triggered when a daily average of the inflow to the ground exceeds the outflow of water from the ground by 125% on a 14-day average. This excludes the inflow of water from other sources.

EstimatedGroundWater=ProcessWaterToGround - ProcessWaterOutOfGround

An alert is triggered when a days mean EstimatedGroundWater is greater than 1.25 times 14D Average EstimatedGroundWater

This approach has been successfully implemented in a large mining organization, with the model being piloted at the mine. Weekly meetings are conducted to review the alerts and get feedback from the users. The alerting logic is fine-tuned to provide better explanations for alerts, which helps improve the model's usage.

CONCLUSION

In conclusion, implementing an AI-based monitoring system for mine dewatering significantly enhances the safety, efficiency, and operational continuity of mining activities. Geological and hydrological complexities often hinder traditional methods for predicting dewatering requirements. The AI approach, incorporating sensor data and Principal Component Analysis (PCA), provides a more robust and accurate detection of anomalies, enabling proactive management of dewatering systems. The static window PCA technique, chosen for its simplicity and effectiveness, generates early alerts for abnormal behaviors such as pump failures and excessive groundwater inflow. These alerts are further refined by an additional monitoring engine, which checks specific system parameters to provide detailed insights.

The successful deployment of this system in a large mining operation highlights its practical benefits, including enhanced safety and improved operational efficiency. Continuous monitoring and feedback mechanisms ensure the system remains adaptive and responsive to changing conditions. This AI-based solution offers a comprehensive and scalable approach to managing the complex challenges of mine water management, setting a new standard for safety and efficiency in the mining industry.

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