Applicability of machine learning in agile decision making in open pit dewatering: A case of study in Antamina mine (Peru)

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Abstract

Numerical models are presented as the fundamental tool for the integration, understanding and prediction of groundwater processes in hydrogeology and mine water activities. However, there are certain difficulties associated with numerical modelling for some cases, such as the management of the dewatering operations in an open pit. Considering that are usually subject to validation and calibration processes of the different hydraulic properties of the medium, in additional to boundary conditions with high uncertainty for large scale study cases, as is usually the case in large mining operations, one can affirm that this process is not simple, requires hydrogeological specialized support and involves a high consumption of calculation time. Not to mention that it is not exempt from a high degree of uncertainty in the predictions obtained due to non-uniqueness inherent to the calibration.

On the other hand, the mining industry is exposed to external parameters beyond its control, such as rains, droughts, and other weather events. This implies having to deal with the uncertainty of nature and requires tools that facilitate agile decision-making in changeable environments that avoid losses such as mining the deepest levels of the pit.

Nowadays, due to the increasing capacity of data collection and storage (big data), artificial intelligence methods and machine learning (ML) algorithms are presented as a promising complement to numerical models in the field of Hydrogeology, especially in mining operations that generate information in numerous networks of points for decades and for which a quick and agile decision making is needed, often monthly.

This paper evaluates the applicability for the management of piezometric and pumping data in a case study on dewatering in an open-pit mining operation in Peru, as well as the predictive potential of ML algorithms to support decisions on expected drawdowns, future well locations and dewatering strategies.

Keywords: Machine learning, hydrogeology, pit dewatering, modelling scenarios

Introduction and motivation

In the advancement of open pit mining operations, one of the essential activities is the planning of dewatering so that operations are carried out in a more efficient and safe manner, assuming that water can be considered one of the destabilizing elements for the walls and slopes that affect and compromise safety (Read & Stacey 2009). Also, operationally, we could list numerous drawbacks associated with inadequate drainage in an open pit, such as accessibility to the pit itself, inefficiency in loading and the weight of the material being transported, transitability of trucks and tire wear or the increase in the use of explosives (Beale & Read 2013). That is why properly planning drainage can generate relevant economic savings, as well as avoid operational delays.

The objective of the work is to evaluate the applicability of machine learning (ML) techniques to estimate piezometric levels based on data series and responses to pumping, as part of the hydrogeological decision-making process in the advancement and development of an open pit.

Antamina, owned by BHP Billiton, Glencore, Teck and Mitsubishi, is located in the Ancash Region, in the Central Andes of Peru. It began operations in 2001 (Fig. 1). Currently, it is one of the largest Peruvian producers of copper and zinc concentrates, as well as one of the ten largest mines in the world in terms of production volume. Their operations have included dewatering management programs since the beginning, including specialized and trained personnel in the hydrogeological discipline, as well as external consultants and reviewers to ensure that drainage activities are carried out appropriately.

The hydrogeological scientific community and engineers specializing in water management in open pits strongly advise on the need to have a robust conceptual understanding acquired by analysis and development of mapping programs, well and piezometer drilling campaigns, performing hydrogeological tests and robust interpretation of the set of information including climatic, geological and hydrological aspects specific to the site and their interaction with the open pit. But at the same time, it is assumed that to date it is true that predictions are commonly developed through numerical models as the fundamental tool for the integration, understanding and prediction of groundwater processes in hydrogeology and mine water activities, such as pit dewatering. However, considering that are usually subject to validation and calibration processes of the different hydraulic properties of the medium, in additional to boundary conditions with high uncertainty for large scale open pits, we can affirm that this process is tedious, long and not at all simple and is very time consuming. Not to mention that it is not exempt from a high degree of uncertainty in the predictions obtained due to non-uniqueness inherent to the calibration.

Antamina's development program constantly seeks efficiency and the use of

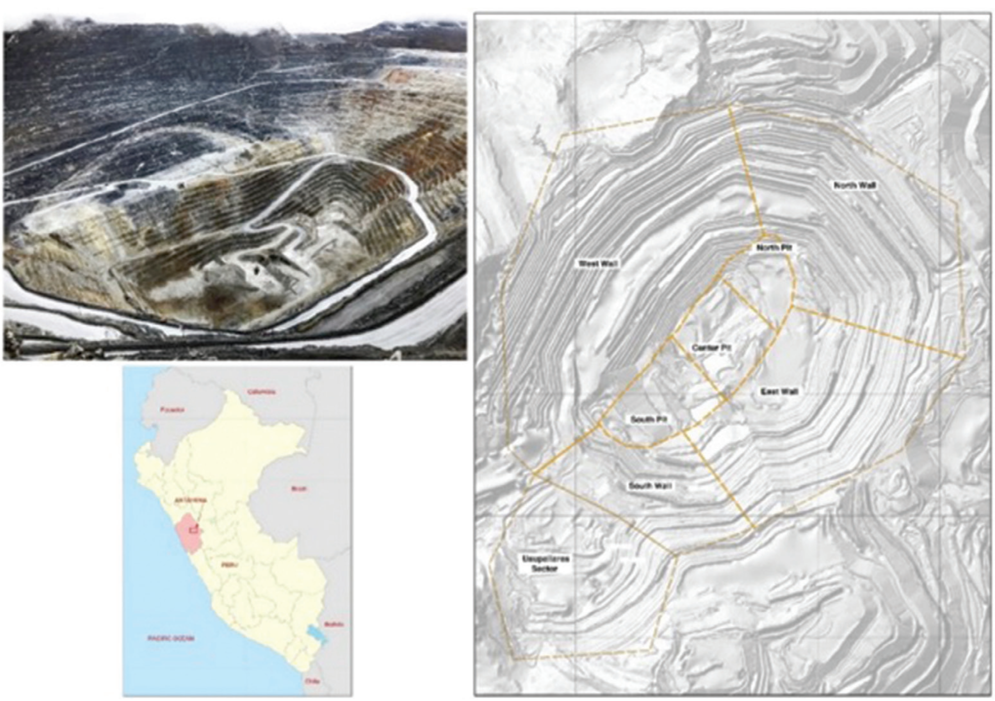

Figure 1 Location of Antamina mine in the Central Andes of Peru, Ancash Region, including an image of the pit layout, as well as the nomenclatures used to segregate behaviours for geological-geotechnical and hydrogeological management

emerging digital technologies for their potential use in operational activities. It is under this framework where the evaluation on the applicability of using ML techniques to predict the future evolution of the groundwater level at a given point in the pit comes into play as a basis for predicting flow rates (dewatering rates) and favourable locations for wells, according to the mining plan.

Brief state-of-the-art

In recent years, artificial intelligence has been used for groundwater resources in several applications specifically for predicting water levels (Tao et al. 2022). ML models are proven to produce comparable and even better results that numerical models especially when dealing with high dimensional and non-linear hydrological relationships. The algorithms can be more flexible, can handle more complex data, and can be used to develop better prediction models (Muhamad et al. 2023). The state-of-the-art in this field involves several innovative approaches and methodologies: ML models (where Artificial Neural Networks or Random Forests algorithms are extensively used), deep learning models (mainly with Convolutional Neural Networks and Recurrent Neural Networks and used for forecasting groundwater levels which are influenced by various temporal and spatial factors), Hybrid Models (combining and coupling ML models with traditional hydrological models) and coupled ML techniques (ML models with optimization algorithms). A review on this in Zounemat-Kermani et al. (2020).

In mining water problems, artificial intelligence has been applied in water quality problems (Sakala et al., 2020; Vadapalli, 2020) but less developments have been done in mine dewatering problems. Ngoie (2017) in a thesis development to that problem concluded that ML algorithms (ANN) were able to successfully predict the general behaviour of the aquifer system under dewatering conditions, using limited input data and illustrated the potential of using ANNs to predict aquifer responses during dewatering operations.

A methodology based on machine learning

A workflow was developed to predict groundwater levels in open-pit mines. This involved integrating historical piezometric level data and pumping records (Fig. 2) with ML techniques to forecast future groundwater levels at a specific point. For this hybrid methodology, it is highly recommended the work to be integrated, always counting on specialized monitoring providing the hydrogeological sense of the conceptualization and operation in the open pit activities, by hydrogeologists who have a background in the project.

1) Initial data handling

As an initial activity, the project began with data processing and management. In data automation and digestion, a suite of scripts (in Python) was developed specifically designed to automatically collect and process the data necessary for the future model. The programming objective of the scripts is to facilitate the reading of data from multiple sources, including piezometric level records and historical pumping data. Automating data collection makes it substantially easier to update the model with new information generated in the future for predictions.

2) Initial statistical analysis

The authors, involved in the development of the hydrogeological activities of the Antamina pit during recent years, managed the information to carry out a detailed statistical analysis of historical data, crucial to understand trends, variabilities, and correlations between different parameters. This analysis also focuses on the development of the algorithms necessary for the project by ML specialists.

3) Conceptual model

The conceptual model, which is the core of this workflow, combines traditional analytical methods with advanced ML techniques. The goal is to provide an accurate prediction of piezometric levels based solely on future pumping plans. The model has two main stages: the analytical approximation and the correction using machine learning.

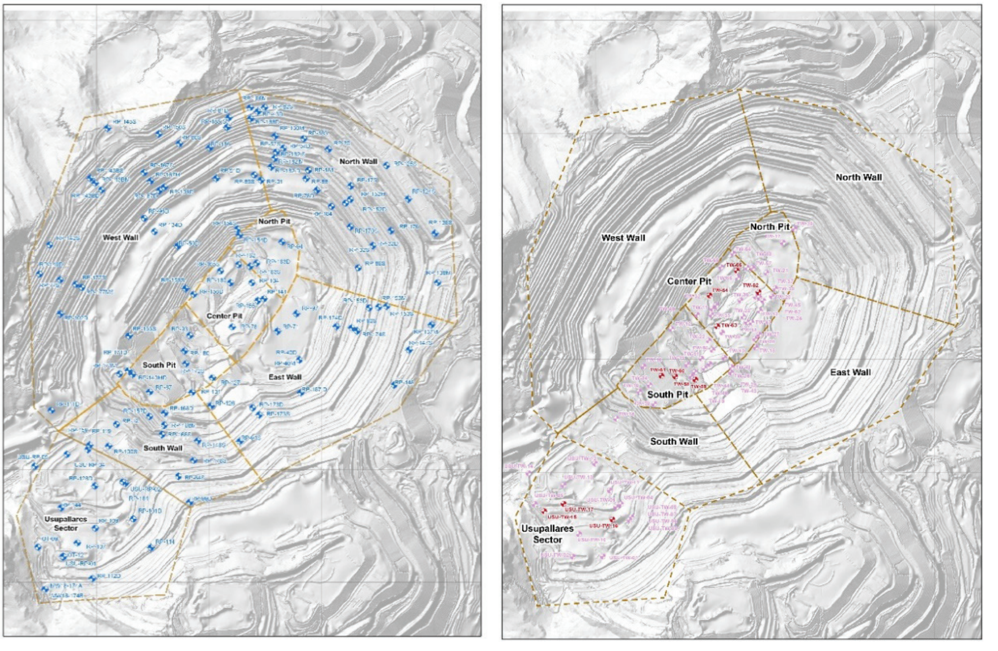

Figure 2 *Historical set of piezometric points (left) and pumping wells (right) used for machine learning model. The series must be properly treated and integrated for their management*

Analytical approximation

Theoretical basis: This is based on solving equations that model the effects of interference from several wells on piezometric levels, using well interference solutions as a starting point.

Parameter optimization: Key parameters involved in the model, such as aquifer transmissivity and storage, have been optimized to estimate historical piezometric levels as accurately as possible.

Optimized variable maps: Transmissivity and storage parameters have been optimized for each piezometer, allowing us to create a map of optimal values. This helps estimate these parameters' values in other nearby areas of the pit, applying the model to intermediate points (an example on Fig. 3).

Machine learning correction

Motivation: While the analytical approximation provides a solid foundation, its accuracy is limited by the system's complexity and temporal variations. This is where machine learning comes into play.

Use of Recurrent Neural Networks (RNN): RNNs are particularly effective for handling time series as they can 'remember' past events and recognize temporal patterns. This ability makes them ideal for adjusting and improving piezometric level predictions.

Inputs: include pumping data (flow rates) and water levels predicted by the analytical approximation for the last 30 days.

Processing: The network analyzes this data to identify patterns and discrepancies between the analytical prediction and the actual piezometric levels.

Improved output: From this analysis, the neural network then adjusts the initial level prediction, improving its accuracy and reliability.

Workflow of the Model

Definition of the pumping plan by the user: The user specifies the future pumping plan according to their experience and pilot tests during drillings.

Application of the calibrated analytical solution: The calibrated analytic solution is used to estimate initial levels at a given point.

Correction with the trained machine learning model: This initial approximation is after adjusted and improved using the

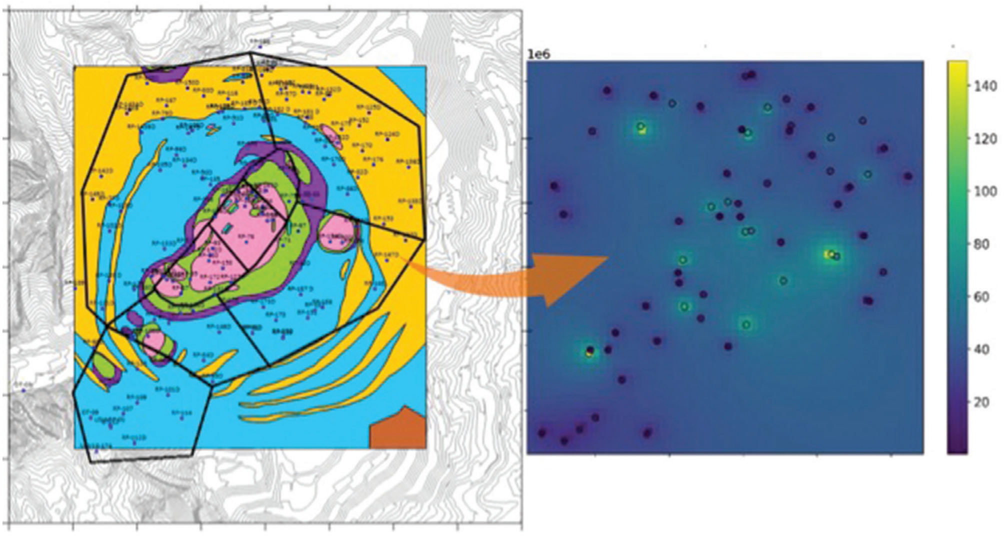

Figure 3 Example of generating hydraulic parameters (in this case hydraulic transmissivity) optimized for the different sectors of the open pit

previously developed and trained machine learning model.

This conceptual model represents a hybrid and advanced approach to predict piezometric levels, combining the rigor of analytical methods with the flexibility and learning capability of machine learning. It could be said that this hybrid methodology would try to capture the physics of the system (through the analytical solution) and at the same time offer a solution that adapts to the peculiarities of the real system (through the ML solution).

Exploitation and use

The model developed for predicting piezometric levels in open-pit mines is characterized by its ability to provide quick and accurate predictions, crucial for practical application in open pit management in mining.

1) Web platform

The model has been implemented on a web platform that provides easy and convenient access for users. This platform allows users to enter their pumping plans and quickly receive piezometric level predictions (Fig. 4). It was designed to be intuitive and easy to use, even for users without advanced technical experience, and can be accessed via a mobile device which allows users in the operational areas of the pit or outside the mine premises to make specific queries.

The platform clearly and concisely displays relevant level graphs for each piezometer and the predicted decline, both by the analytical approximation and the integrated solution if the user requires it.

2) Well prediction rates according to the LOM

The hybrid model is being used in a complementary manner for bimonthly to six-months predictions to evaluate the performance of the current dewatering system to achieve the mining progress targets according to the planned LOM. The needs and potential locations of future wells are evaluated when the progress itself leads to the elimination of some of the existing wells, thus supporting future CAPEX decisions (Fig. 4).

3) Advantages of using machine learning

Post-training efficiency: Once the machine learning model is trained, it can generate predictions almost in real time. This speed is crucial in situations where management decisions need to be made quickly.

Adaptability to different pumping scenarios: Users can modify and experiment with different pumping scenarios, and the

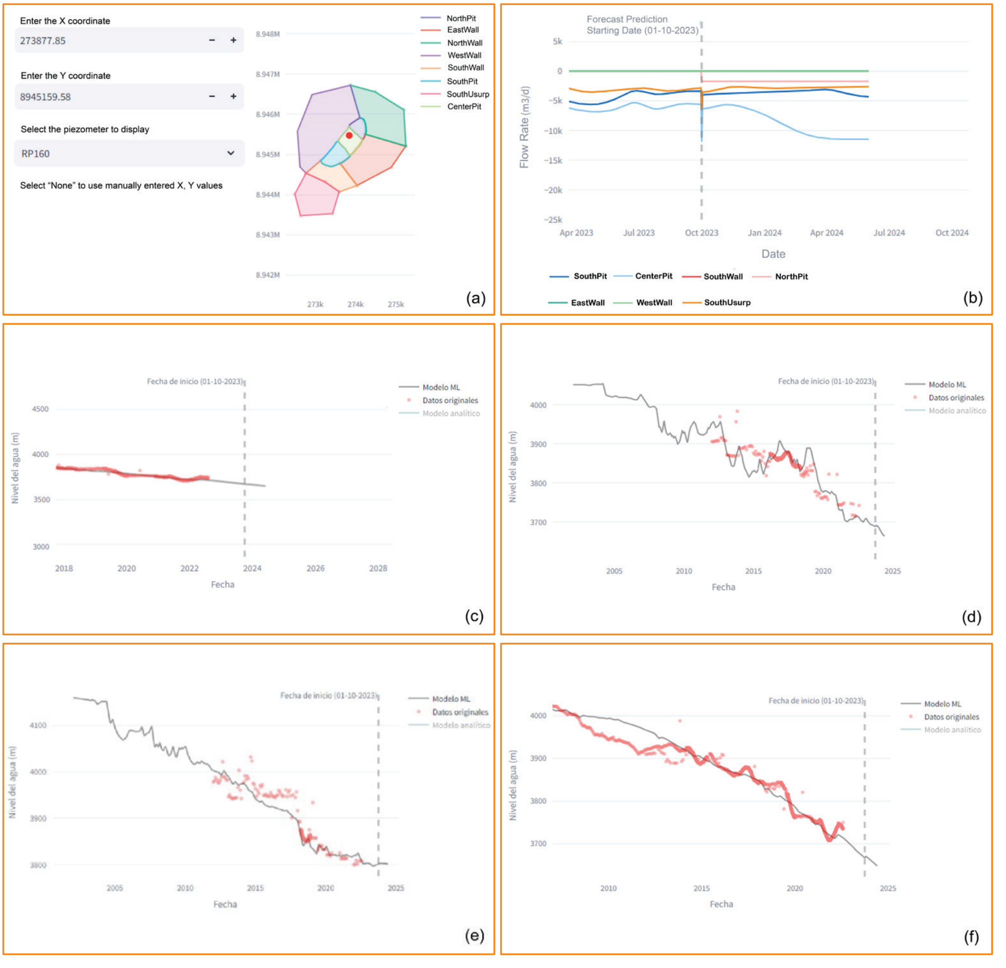

Figure 4 Example of a forecast simulation (six-month period) in the web platform (a). On the right (b) one can see the extraction flow rates at different pit zones. Figures c, d, e, f show predicted drawdowns on some of the monitoring piezometers to support potential well locations

model will quickly provide new predictions, facilitating the optimization of water management strategies.

Refinement of ML algorithms: There is always room for improvement in Machine Learning, and it is a rapidly advancing technology. Continuous development and adjustment of ML algorithms, exploring new neural networks, architectures, etc. could increase the model's accuracy and reliability.

Future add-ons: Possibilities for improvement include the introduction of cost variables, which in the future could complement predictions, those that allow optimization of operating costs.

Conclusions

This paper evaluates the predictive potential of ML algorithms in a case study of dewatering in an open pit mining operation in Peru. The results obtained from the application have shown that artificial intelligence technologies present (i) a satisfactory predictive capacity, (ii) they can be quick and effective tools in making decisions about the influences of production wells during development of open pit mine dewatering and (iii) can be applied as support in the planning for the water operations in the pit.

This complementary methodology has been presented to support decision making in the advancement of dewatering operations and the aim is not to replace classic methodologies based on numerical approximations, but rather to complement them, particularly for agile and rapid decisions where ML techniques can be more easily adaptable.

As with numerical models, it is recommended that the ML-based hybrid model presented be developed with the knowledge and particularities of the site, especially the geology and the assignment of hydraulic properties to the different units, a set of piezometric data and of pumping that is sufficiently extensive and that is validated by specialists with knowledge of the operation and the evolution of the pit under study.

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