frontiers | Frontiers in Earth Science

MINI REVIEW
published: 06 April 2022
doi: 10.3389/feart.2022.816751

Mineral Leaching Modeling Through Machine Learning Algorithms – A Review

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Artificial intelligence and machine learning algorithms have an increasingly pervasive presence in all fields of science due to their ability to find patterns, model dynamic systems, and make predictions of complex processes. This review aims at providing the researchers in the mineral processing area with structured knowledge about the applications of machine learning algorithms to the leaching process, showing the applications of techniques such as artificial neural networks (ANN), support vector machines (SVM), or Bayesian networks (BN), among others. Additionally, future perspectives are indicated, emphasizing both the generalization of the algorithms and the productive potential of the application of modeling, simulation, and optimization of the tools studied to industrial processes.

Keywords: mineral leaching, modeling, machine learning, artificial inteligence, algorithms

OPEN ACCESS

Edited by:
Mohammad Parsa,
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Reviewed by:
Farzaneh Mami Khalifani,
University of New Brunswick Fredericton, Canada

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Specialty section:
This article was submitted to Economic Geology, a section of the journal Frontiers in Earth Science

Received: *17 November 2021*
Accepted: *22 March 2022*
Published: *06 April 2022*

Citation:
Saldaña M, Neira P, Gallegos S, Salinas-Rodríguez E, Pérez-Rey I and Toro N (2022) Mineral Leaching Modeling Through Machine Learning Algorithms – A Review. Front. Earth Sci. 10:816751. doi: 10.3389/feart.2022.816751

INTRODUCTION

World copper mine production decreased slightly to an estimated 20 million tons in 2020 from 20.4 million tons in 2019, mainly due to the COVID-19 blockages in April and May. These disruptions significantly affected production in Peru, the second largest copper mining producer, where production through July 2020 was down by nearly 250,000 tons (23%) from the same period in 2019. World refined copper production increased slightly to an estimated 25 million tons in 2020 from 24.5 million tons in 2019, when production in several countries was affected by temporary smelter shutdowns for maintenance and upgrades (Flanagan, 2021). Then, copper production in Chile in 2020 was around 5.73 million tons, which is disaggregated into 3,058 million tons of concentrate, 1,468 million tons of SX-EW cathodes, and 1,206 million tons of smelter copper (Consejo Minero, 2021).

Most of the copper ores on the planet correspond to sulfides and a small part to oxides (Hernández, 2013). The mining industry has traditionally operated in two ways, pyrometallurgy in the case of sulfide ores, consisting of flotation, smelting and electro-refining processes. While hydrometallurgical processes have worked mainly with oxidized ores, composed of leaching, solvent extraction and electrowinning (Schlesinger et al., 2011). Both working mechanisms have proven to be profitable in the industry, however pyrometallurgy has the disadvantage of generating SO_2 emissions to the atmosphere, generating serious environmental problems (Sosa et al., 2013). However, it is expected that the implications of the technological revolution in mining will contribute to mitigate the negative effects of mining on the environment (Wood et al., 2021).

Considering the above, and the significant number of mining sites operating hydrometallurgical processes in Chile, the study of processes such as leaching, and the search for tools that contribute to improve their efficiency and effectiveness through modeling, simulation and/or optimization, either through mathematical models or based on machine learning, could have the potential to contribute to achieve a better understanding of the dynamics of the process and improve production indicators.

Leaching processes can be defined as the selective removal and/or extraction of metallic values from an ore by causing a suitable solvent or leaching agent to leach into and through a mass containing the ore (Ghorbani et al., 2016). In the present work, a comprehensive analysis of scientific modeling techniques of the leaching process using machine learning techniques is developed. Models are of vital importance in many scientific contexts, which spend a great deal of time building, testing, comparing and revising models, and much journal space is devoted to interpreting and discussing the implications of such models (Roman and Hartmann, 2006).

A generic definition of a scientific model is that they are representative models, which represent a particular part or aspect of the world, which is the target system, and a tangible result of philosophical engagement with models is a proliferation of recognized types of models in the philosophical literature (Roman and Hartmann, 2006). A scientific model is then a physical and/or mathematical and/or conceptual representation of a system of ideas, events, or processes. Scientists seek to identify and understand patterns in our world by drawing on their scientific knowledge to offer explanations that predict patterns. The models created by scientists must be consistent with our current observations, inferences, and explanations. However, scientific models are not created to be factual statements about the world. Therefore, the most important results of developing a mathematical model of a chemical engineering system (such as heap leaching) is the understanding gain of what actually makes the process "work". This information allows to remove the many extraneous "confounding factors" from the problem and get to the heart of the system by identifying the cause and effect relationships between variables (Benenati, 1973).

Therefore, the aim of this review is to identify the advances of applications of artificial intelligence algorithms to the mineral leaching process, for which the process is generally described in *Leaching Process* Section, the findings of applications of ML techniques to the leaching process are described in *Modeling of the Mineral Leaching Process* Section and, finally the future perspectives at industrial level and conclusions are presented in *Concluding Remarks and Future Works* Section.

LEACHING PROCESS

Leaching is defined as the 'treatment of complex substances, such as an ore, with a specific solvent to separate its soluble parts from the insoluble ones' (CED, 2021). One of the most widespread applications is the mineral leaching on an industrial scale through the heap leaching technology, which was developed in the United States, and substantially improved in Chile, achieving industrial applications on a large scale in hydrometallurgical processes.

As part of the process of shaping and processing the pile, the crushed material is transported (generally by conveyor belts) to the place where the pile will be formed. On this route, the material is subjected to an initial irrigation with a solution of water and H_2SO_4, known as the "curing process", with the aim of initiating the sulphation process of the copper contained in the oxidized or sulphide minerals [cured with mixed solutions of sulphuric acid and chlorides (Dutrizac and MacDonald, 1971; Watling, 2013)]. At its destination, the ore is unloaded using a spreader, which deposits it in an orderly way, forming a continuous 6- to 8-m high embankment: the leaching heap. A drip irrigation system and sprinklers are installed on top of this pile, covering the entire exposed area. Under the heaps to be leached, an impermeable membrane is previously installed on top of which a system of drains (slotted pipes) is installed to collect the solutions that infiltrate through the material, as shown in **Figure 1**(Domic, 2001).

Additionally, the bibliometric analysis indicates that all the available information on mineral leaching in the Web of Science reference database shows that there is no significant relationship between machine learning algorithms and leaching, which does not indicate that there are no papers on the subject, but rather that the number of target papers is not large. The visualization of the network indicates the existence of different clusters focused on leaching, process kinetics and mineralogy. However, it is worth highlighting the existence of the mathematical models' node (see **Figure 2**), which considers the works found in the literature referred to both phenomenological and machine learning-based modeling.

MODELING OF THE MINERAL LEACHING PROCESS

Research and development in the field of artificial intelligence has led to the use of tools such as machine learning in various fields, due to its ability to model complex systems, learn from observations, identify trends and make recommendations in decision making processes. By implementing machine learning in production processes, through the generation of digital twins of processes such as leaching, it is possible to understand the dynamics of the process, identify variables of interest and optimize responses in an industry that will incorporate end-to-end technologies in its production chain, improving the efficiency and control of processes such as fragmentation, leaching or any subprocess of the production model, incorporating highly selective, efficient, flexible and clean methods of mineral processing and mining (Dunbar and Klein, 2002).

Applications of machine learning techniques applied to mineral leaching modeling can be found in Golmohammadi et al. (2013), where a quantitative study based on partial least squares (PLS) and artificial neural network (ANN) is developed for the prediction of ferric iron precipitation in the bioleaching process, and in Xie et al. (2016), an alumina leaching rate prediction model is established by integrating a kinetic model, and an error compensation model of the kinetic model based on kernel extreme learning machine (KELM) (Huang et al., 2012), an algorithm that introduces kernel leaning into extreme learning

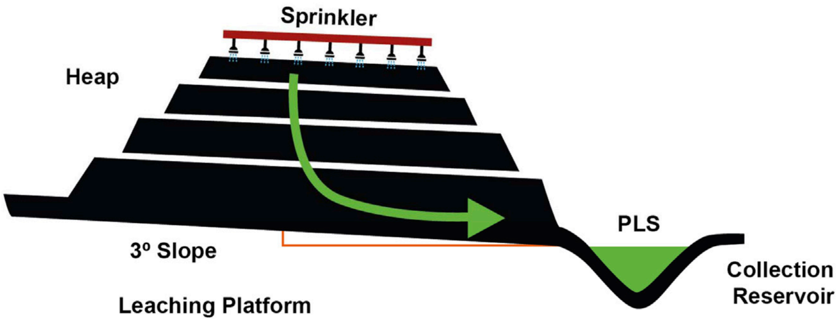

FIGURE 1 | Conventional heap leach pad and high-level operating dynamics.

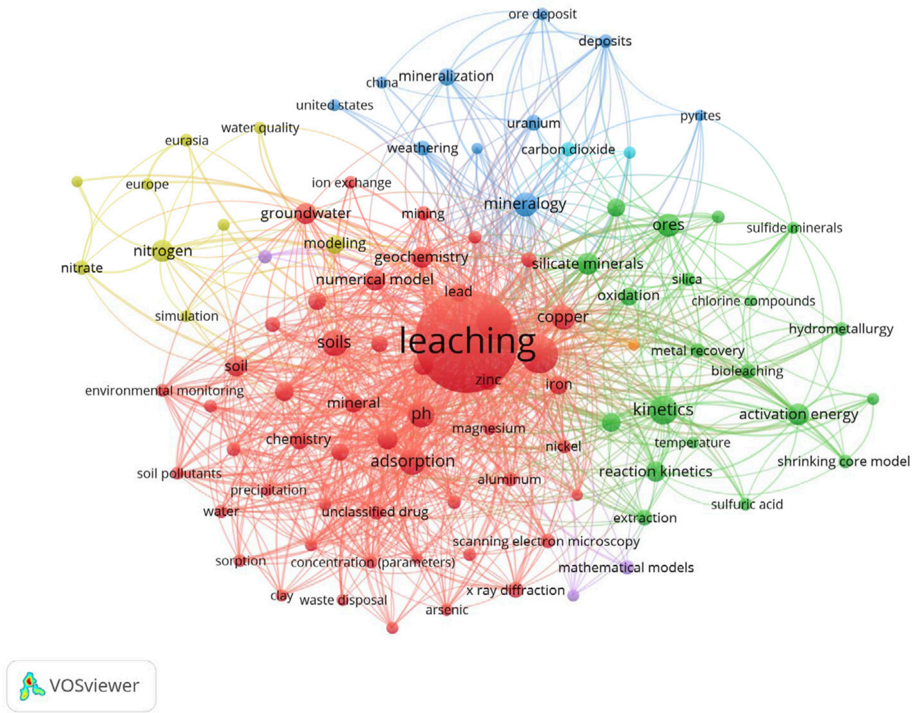

FIGURE 2 | Visualization of networks between keywords of consulted bibliography.

machine (ELM) in order to improve the generalization ability and stability. The verification of the model obtained from the parallel connection of the kinetic model with the compensation model was verified using industrial data, indicating that the integrated model has high accuracy and can successfully predict the leaching rate and its changing trend, and can be used as a basis for simulation and/or optimization.

Subsequently, Niu and Liu (2017) use a least-squares support vector machine (LS-SVM) based on the just-in-time (JIT) algorithm to build the leaching rate prediction model, when multivariate multimode nonlinear characteristics of the hydrometallurgical leaching process are considered, showing that the proposed method has high accuracy in predicting the leaching rate.

In Leiva et al. (2017), a soft computing framework is used to model copper recovery in the heap leaching process, using regression models (linear, quadratic and cubic) and ANN's. Then, in Flores et al. (2020), artificial intelligence algorithms based on Random Forest (RF) are used to predict copper recovery by leaching, which is extended in Flores and Leiva (2021), where a comparative analysis is made between three machine learning models (RF, SVM and ANN), to predict copper recovery by heap leaching, concluding that the model based on artificial neural networks has a better performance when representing nonlinear models such as the one studied.

Some applications examples in mineral processing where RF is used, is in leaching modeling (Demergasso et al., 2018; Lillington et al., 2020), or mineral prospectivity (Parsa and Maghsoudi, 2021).

In Lillington et al. (2020) machine learning is applied to predict the behavior of static glass leaching from large data sets, corroborating the power of the algorithm to correlate large-scale leaching process data, while Demergasso et al. (2018) model the industrial-scale heap bioleaching process, developing a systematic approach using machine learning tools (classification/decision tree model) for high-dimensional feature space analysis to provide experience-based learning to serve as a basis for optimal production planning and operational decision making in the presence of inherent process variations.

Then, in He et al. (2019), a gold cyanidation leaching process characteristic (GCLP) change recognition system is developed using principal component analysis (PCA) for mismatch detection of the GCLP process function, and SVM to recognize the type of process characteristic change, provide guidance for its treatment and help make corrections to the model.

In contrast to the methods indicated above, in Saldaña et al. (2019b), stochastic modeling of the heap leaching process is developed by generating a Bayesian network, a tool that, in addition to describing the mineral recovery as a function of the independent variables, allows the identification of the dependence or causal relationships between the explanatory variables. Another interesting point to highlight in the work developed by Saldaña et al. (2019b) is the ability of Bayesian networks to infer the response or generate estimates based on partial knowledge of the input variables. Additionally, and in the same line of Flores et al. (2020), Saldaña et al. (2021) uses the RF algorithm to develop an inference engine to represent the dynamics of the process, together with predicting how the stack operates. In Shoppert et al. (2020) an ANN-based model (specifically a multilayer perceptron) is applied to model the effect of leaching conditions on the efficiency of fly ash desilication (FA). The aim of the study was to show the possibility of increasing the degree of SiO_2 extraction from fly ash desilication by NaOH leaching while reducing NaOH loss with solid residue by keeping Al_2O_3 in the leach.

On the other hand, Spijker et al. (2021) developed a machine-learning-based modeling framework to predict nitrate leaching from Dutch agricultural soils, using the Random Forest algorithm as a prediction and interpolation method. The use of ML algorithms allows the spatial variability of nitrate concentrations to be identified, however, it should be noted that the algorithm used can only be used as a predictive tool in areas where data are available, given its lack of robustness in extrapolation. Subsequently, Bailey et al. (2021) use a machine-learning-based approach to segment X-ray computed tomography data sets using ML techniques to investigate phosphoric acid leaching in high temperature polymer electrolyte fuel cells. The segmentation performed by Bailey et al. (2021) aimed to classify digital images using ilastik (Sommer et al., 2011), software that uses a RF classifier in the learning step, where the neighborhood of each pixel is characterized by a set of generic (nonlinear) features.

Finally, it is only worth highlighting the potential of the tools generated by the digital revolution and artificial intelligence in the transformation of production processes, including better visualization, transparency, integrated planning and execution for the optimization of the value chain, resulting in smarter production (Steyn et al., 2019).

CONCLUDING REMARKS AND FUTURE WORKS

Mineral leaching is a solid-liquid extraction process, where a liquid in the presence of a solvent extracts one or more soluble components, resulting in a rich liquid substance. The high-level modeling of the process has been carried out by several authors, mainly using mathematical or phenomenological models (Dixon and Hendrix, 1993a; Dixon and Hendrix, 1993b; Dixon and Hendrix, 1993c), and adjustments of these have been used to integrate intelligent recommendation systems to support decision making (Demergasso et al., 2018; Saldaña et al., 2019a, 2021).

Artificial intelligence algorithms have demonstrated their superiority in the modeling of complex systems, being widely applied in mineral processing, as evidenced by the works of Rodriguez-Galiano et al. (2015), McCoy and Auret (2019), and Jung and Choi (2021). Machine learning is revolutionizing the way of modeling, simulating and optimizing production processes, due to its ability to predict non-conformities, reduce downtime, improve efficiency by identifying bottlenecks and suboptimal operating states, and increase efficiency and productivity, among others.

Then, modeling of mineral leaching should advance to generate digital twins that consider a greater amount of information in the feed (more independent variables), with the objective of reliably abstracting the real dynamics of the process, for which, in addition to adjust different algorithms, such as clustering, neural networks, decision trees or derivatives, Bayesian networks (stochastic modeling), it could incorporate the model assembly method, or combined methods (not developed or applied to mineral leaching in the literature so far), which help to improve the performance of machine learning models by improving their accuracy. Ensemble methods are methods by which several machine learning models are built, and once combined or aggregated, used to solve a particular problem, such as modeling, simulation and optimization of the dynamics of the mineral leaching process.

Finally, the application of innovations such as the tools provided by advances in artificial intelligence (either through the generation of exploratory or predictive models) has the potential to optimize hydrometallurgical operations in the mining industry.

AUTHOR CONTRIBUTIONS

MS and NT contributed in research and wrote the paper, PN, SG, ES-R, and IP-R contributed with research, review and editing. All authors have read and agreed to the published version of the manuscript.

ACKNOWLEDGMENTS

MS acknowledges the infrastructure and support of Doctorado en Ingeniería de Procesos de Minerales of the Universidad de Antofagasta.

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