Soft Computing Application in Mineral Processing

Subjects: Mining & Mineral Processing

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The mining sector has increasingly embraced simulation and modelling techniques for decision-making processes. This adoption has facilitated enhanced process control and optimisation, enabling access to valuable data such as precise granulometry measurements, improved recovery rates, and the ability to forecast outcomes. Soft computing techniques, such as artificial neural networks and fuzzy algorithms, have emerged as viable alternatives to traditional statistical approaches, where the complex and non-linear nature of the mineral processing stages requires careful selection.

mineral extraction soft computing process control prediction accuracy

1. Introduction

The mining industry contributes to approximately 10% of global economic activities, of which industry payments for services and direct support comprise another 10%, making it a critical part of multiple production chains [1]. Over time, this industry has been a precursor for technological developments. According to the European Parliament [2], during the past 12 years, a quarter of the mining industry has doubled its investments in technology, reaching 93% implementation with successful results. Over 90% of mining companies believe that complementing their operations with technology translates into added value and helps to revolutionise their business. The advancement of technology has led to the emergence of untapped prospects in the field of big data capture systems, which have not yet been fully explored or utilised in industrial settings. For instance, these systems can be employed for routine inspections of operational equipment or for the creation of daily production records [3]. This volume of data is expected to grow exponentially over time, reaching an amount of one hundred and twenty zettabytes in 2023, corresponding to a 675-fold increase since 2005 [4][5][6].

The mining industry and metallurgical processes are familiar with the concept of capturing large amounts of data. However, the analysis and interpretation of this data present novel problems for operators and decision-makers who aim to enhance productivity and sustainability in their operations. The European Union has set four key goals for the year 2030, as outlined by Usman et al. [7], which include prioritising energy efficiency, reducing CO_2 emissions, and promoting the adoption of clean energy sources. To achieve these objectives, the EU emphasises the importance of sustainable raw material production through the utilisation of digital tools, as well as advancements in safety, productivity, and profit margins [8]. While the World Economic Forum has predicted that from 2017 to 2025, $425 trillion will be invested globally in the application of artificial intelligence (AI) for the productive sector [9], in Chile, the creation of national policies and initiatives such as the Roadmap Mining 4.0 [10] policy seeks to implement digital technologies in the mining industry. There is a correlation between artificial intelligence (AI), Mining 4.0, and machine learning technologies that can potentially drive transformative advancements in mining processes, enhance productivity, and enable data-driven decision-making in an increasingly interconnected and digital world.

2. Performance of Soft Computing Applied in Mineral Extraction and Processing

Figure 1 illustrates a comparison of the soft computing techniques employed in the stages analysed early and based on the total number of publications. The performance of each method is evaluated based on four criteria: accuracy, reliability, correlation values, and computational efficiency. The scores are based on accuracy values, with higher scores indicating better accuracy; reliability scores are based on mean residuals and standard deviations in the papers; correlation scores are based on correlation coefficients; and computational efficiency scores are based on the characteristics and advantages of the methods in the papers.

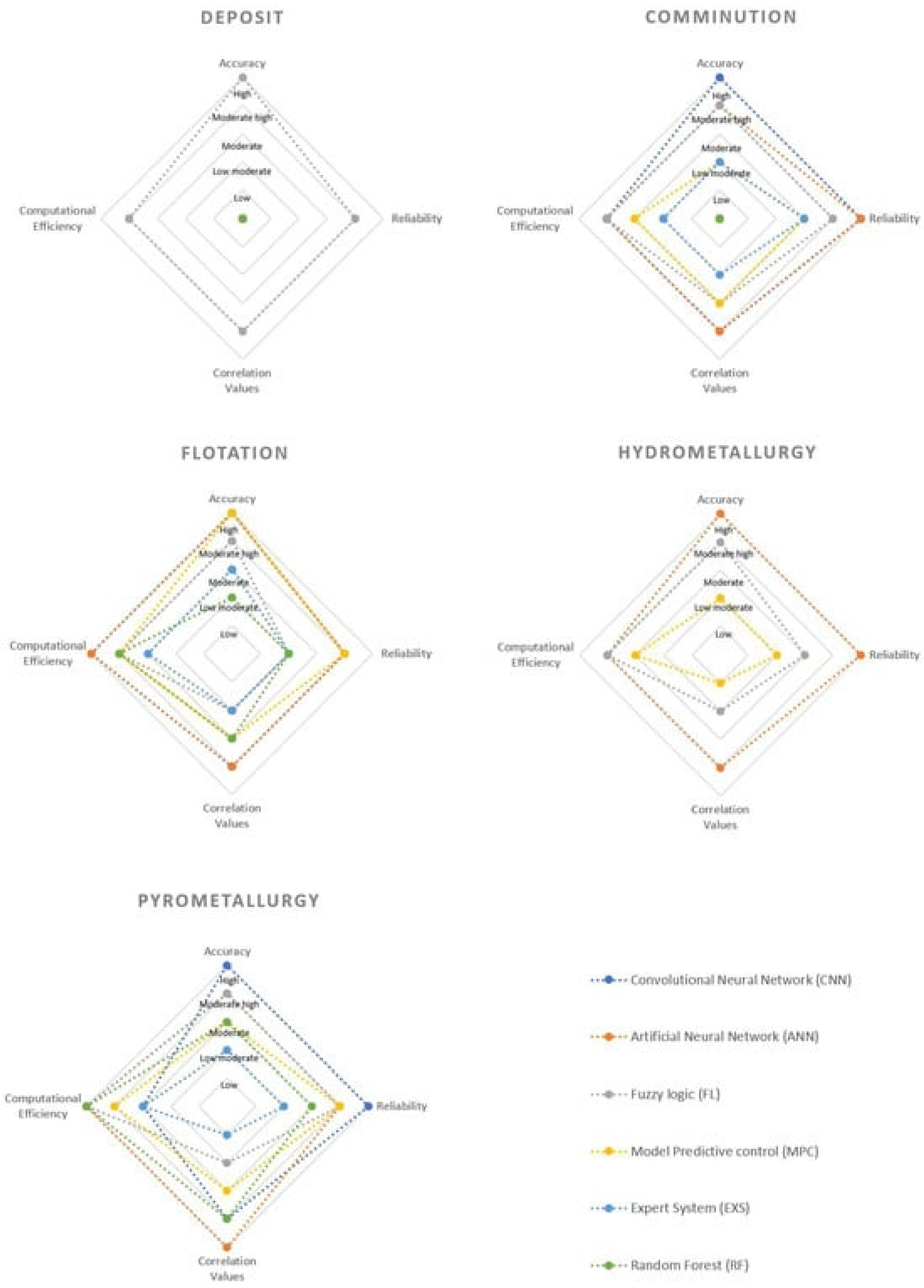

Figure 1. Qualitative comparison of soft computing methods applied in mineral processing.

Across the five stages analysed, convolutional neural networks (CNN) consistently exhibited robust performance, often achieving strong accuracy and reliability in comminution and flotation processes and exceeding relevant reliability while maintaining competitive correlation values and computational efficiency. Artificial neural networks (ANN) also demonstrate strong performance with high accuracy ratios, and they maintain competitive correlation values and computational efficiency, especially in pyrometallurgical processes. For hydrometallurgical processes, ANN emerges as the most favourable option, with relevant accuracy and reliability. Fuzzy logic (FL) excels in accuracy in mining stages, showcasing its capability, but it shows a drop in reliability if it is applied in flotation stages. Model predictive control (MPC) and expert systems (EXSs) display moderate to good performance across all the processes, reflecting their reliability across different situations and data variables. Random forests (RFs) show variable performance, with their highest accuracy at 60% in flotation stages and fluctuating reliability and correlation values, indicating their versatility but also their inconsistency. The artificial neural network (ANN) method appears to be a common method that can be applied in all stages, performing well in the criteria for all stages except for hydrometallurgical processes, where the CNN method performs slightly better in terms of accuracy and reliability and FL stands out as a versatile choice.

3. Proposed Approach for the Application of Soft Computing in Waste Disposal in Mineral Extraction and Processing

One critical challenge to ensuring medium- and long-term operation is to achieve the adequate disposal and management of mining tailings (Residues from sulphide mineral flotation composed of material without the mineral of interest and water that are disposed in specific deposits known as TSF) and spent heap leaching spoils (Material that remains as a residue from the heap leaching process once all of the mineral of interest has been recovered). This has been declared as critical within the sustainability and responsible operation programs by the European Union to ensure proper management to avoid damaging the environment [11][12]. The incorporation of better technology for tailing storage facilities (TSFs) and spent heap leaching spoils dumps (leaching waste deposit, LWD) and the development of mechanisms for the measurement of parameters and variables are the final objective in controlling physical and chemical stability monitoring systems and establishing a robust understanding of the makeup and water balance of the process. In Chile, copper production as a concentrate will reach 89.9% in the year 2027 due to the depletion of oxidised copper minerals [11], while the use of continental water consumption exceeds 0.36 m^3/ton of ore, with the consumption expected to rise further [13]. The application of soft computing to waste disposal may provide quality, reliable, and real-time information on the waste ore and tailings according to the operational needs. In addition, authorities and communities may benefit from the accessibility of this information, to improve, make transparent, and strengthen the ties between the industry and the communities, taking an important step to comply with national legislation and to improve the sustainability culture.

The proper management and ultimate disposal of these wastes is critical to the continuity of the profit chain and are linked to a successful storage operation, adequate use of land, security, and, in a relevant way, to the environmental commitment of the mining operation. In countries with a mining tradition, such as Chile [14], Finland [15], and Canada [16], regulations and guides provide information to design, install, and manage waste rock dumps and TSFs focused on the beginning of the deposit creation, leaving the subsequent monitoring and control of these deposits to their own criteria against structural behaviour, physicochemical stabilization, and mitigation of possible failures. Industrial practices and the changes that take place in a dynamic operational environment mean that on many occasions the original design is strongly modified for safety or even does not reach the useful life that was originally planned. The stability of a tailings storage facility (TSF) can be influenced by [17][18]:

- Operating factors (input material, deposition rate, geometrical and geotechnical controls such as humidity and compaction).
- Deposit location (climate and geological factors that include the seismicity, ground foundation slope, and confinement of the land degree)
- Deposit type selected (type of the TSF, geometric configuration including height, volume, and slope angle)

Establishing the use of soft computing to advance the “mining digitalization” of processes such as the monitoring of mining tailings and spent heap leaching spoils transport and deposition is a solution that could be non-invasive and consistently obtain a higher quality control and constant evolutionary knowledge by identifying the most influential variables in these processes, minimising possible prediction errors. A dependency on the tailings and spent heap leaching spoils disposal fluency behaviour can be established based on the dynamic mineralogy of the ore and rheological and permeability characteristics. In the case of tailings, the presence of specific clays and changes in the solid concentration in the thickener discharge cause changes in the TSF behaviour, modifying the established area and volume of the disposal, changing the functionality and possibly creating environmental impacts. The evaluation of these parameters with soft computing enables correlation and identification of a behavioural pattern. This implementation can also serve as an update for operational decisions related to environmental demands in countries with a mining tradition, such as Chile and Finland. These countries have recognised the significance of valuing existing data and conducting thorough analysis in order to inform operational decision-making processes.

A prior analysis must be generated to help identify the impact generated by the conditions used in the operation and that will translate into the tailings and spent heap leaching spoils behaviour. An alternative used to identify these variables corresponds to the application of a correlation, and thereby establishes the combination of variables to be used with soft computing tools such as ANN or CNN. Then, the parameters of the new empirical model are adjusted in a very precise way, using only the new measurement data from the new model [19]. However, a low level of learning is achieved using this method, since “catastrophic forgetting” can occur, which means that while fine tuning is established in the new model with new data, the historical data performance is drastically impaired due to the discrepancies between the old and new data sets [20]. Retraining also uses the weights from the existing empirical model and uses it to create a new empirical model; unlike data fitting, the parameters of the new empirical model are precisely adjusted using historical data and current data from the new model from a simultaneously [21]. This scope can solve the “catastrophic forgetting”; however, this method needs important periods of time in order to update the data continuously [22]. This analysis also raises the question of whether, if a robust database could be established with data from different mining operations, it could find common ground between the studied cases that could be correlated between the different operations considering critical mineralogical factors such as the presence of clays and changes in rheological behaviour due to the medium used, such as fresh water or sea water. Naturally, this presents the potential to manage different perspectives to find the right path in the soft computing application. For example, the application of an incremental method aims for the “excitation” patterns of a new process to be accommodated without compromising the performance of the patterns of a process with historical data. In general, this type of method adapts new patterns by designating new constraints or constant rules to modify the adjustable parameters of the updated model. It is more efficient than a retraining method because the empirical model does not need to be trained on all historical data [23].

The use of incremental learning as a part of an artificial neural network can be a real option considering the flexibility in the quantity and interaction of the input nodes that can be applied, but also considering the time and application capacity given the available data and the operation monitoring frequency used at an industrial level. An opportunity to use ANN for operational decision-making lies in the existing monitoring capacity of the variables related to the mining waste operation, access to this information, and how robust this data is. As part of the analysis, **Figure 2** illustrates a proposed database generation to analyse the most appropriate application of soft computing in the deposition of the tailings and spent heap leaching spoils. This database will serve as the foundation for conducting a preliminary stage of weight identification for each variable, followed by subsequent analysis.

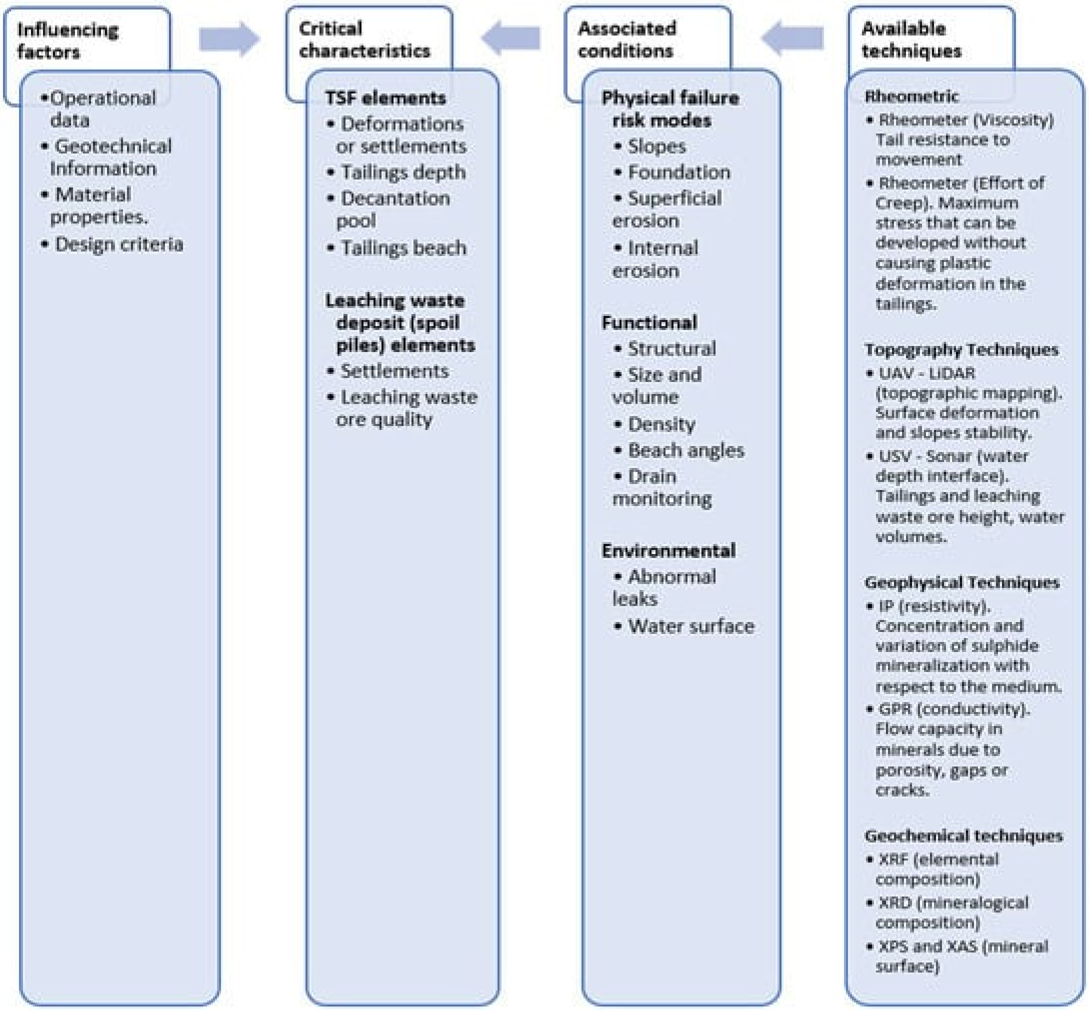

Figure 2. Parameters for a database generation for TSF and LWD.

Figure 3 presents an analysis framework that explores potential connections using various soft computing techniques, including neural networks. This framework incorporates training, prediction, and confirmation stages.

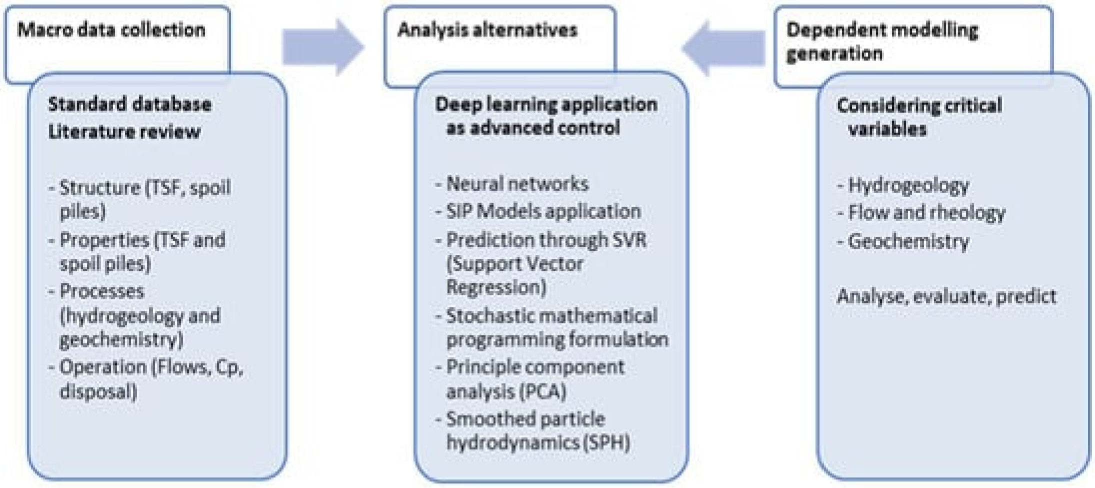

Figure 3. Example of possible correlations between parameters with different soft computing techniques.

As is shown, the proposal emphasises the importance of standardising the database for macroscopic data collection, considering the structure, properties, processes (hydrogeology and geochemistry), and operation (flows, Cp, disposal) as possible options for input data modelling. This approach ensures a comprehensive understanding of the parameters involved. A second aspect explores alternatives for deep learning applications in advanced control, emphasising the results obtained from the analysis presented in this publication and including neural networks, SIP model applications, SVR (support vector regression), stochastic mathematical programming formulation, and principal component analysis (PCA). These techniques offer different methodologies and approaches to effectively analysing and controlling the parameters. The third aspect focuses on dependent modelling generation and highlights critical variables for analysis, evaluation, and prediction. Hydrogeology, operational monitoring and rheology, and geochemistry are identified as potential options. By taking into account these variables, one can acquire valuable insights into the interconnectedness among them and make accurate predictions about future behaviour.

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