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Review

Soft Computing Application in Mining, Mineral Processing and Metallurgy with an Approach to Using It in Mineral Waste Disposal

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Abstract: In the past two decades, 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. This research examines the up-to-date use of soft computing techniques within the mining sector, with a specific emphasis on comminution, flotation, and pyrometallurgical and hydrometallurgical processes, and the selection of soft computing techniques and strategies for identifying key variables. From this, a soft computing approach is presented to enhance the monitoring and prediction accuracy for mineral waste disposal, specifically focusing on tailings and spent heap leaching spoils database treatment. However, the accessibility and quality of data are crucial for the long-term application of soft computing technology in the mining industry. Further research is needed to explore the full potential of soft computing techniques and to address specific challenges in mining and mineral processing.

Keywords: mineral extraction; soft computing; process control; prediction accuracy; artificial neural networks; expert systems; fuzzy algorithms; mineral waste disposal; tailings; heap leaching piles

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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 [4–6].

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. The objective of this paper is to reveal the potential in question.

2. Background and Finding the Gaps

Since 2015, the fields of data science and soft computing have significantly contributed to the development of more precise predictive models [11]. The effectiveness of these models is contingent upon the specific characteristics of the problem at hand and the amount of available data. Furthermore, the advancements in computing capabilities have facilitated the widespread adoption and refinement of these tools in various industries and processes, encompassing a wide range of specialties, through the integration of artificial intelligence and statistical techniques. Soft computing is a subfield of artificial intelligence that encompasses various paradigms and techniques designed to handle incomplete and imprecise information in crucial processes. Its primary objective is to enable companies to derive valuable solutions for tasks such as prediction, information discovery, and knowledge acquisition [12,13]. This research aims to examine the application of soft computing in mineral processing, providing a perspective on the operational impact of relevant stages present in the processing lines of valuable minerals and considering the possibility of supporting operational decisions. Based on this review, an application approach to mine waste disposal operations is introduced.

2.1. Automation in the Mining Industry and Opportunities for AI

The mining industry can benefit significantly from the application of AI to enhance process control and improve productivity. The development of sensors, transmitters, and controllers has given way to centralisation of the control and supervision of variables using evolving technologies in control systems (Figure 1) and the development of control loop applications [14]. These systems offer prompt information and rapid responses to external and internal disturbances, guaranteeing a safe and stable operation within the process. The choice of the functions oriented to the analysis of information and the application of superior decisions are fundamental functions for the control and monitoring of the process [15]. The focus of their work lies in the examination of information, and the effectiveness of their decision-making process is contingent upon the execution and necessity of decisions and problem-solving tasks that lack algorithmic resolutions.

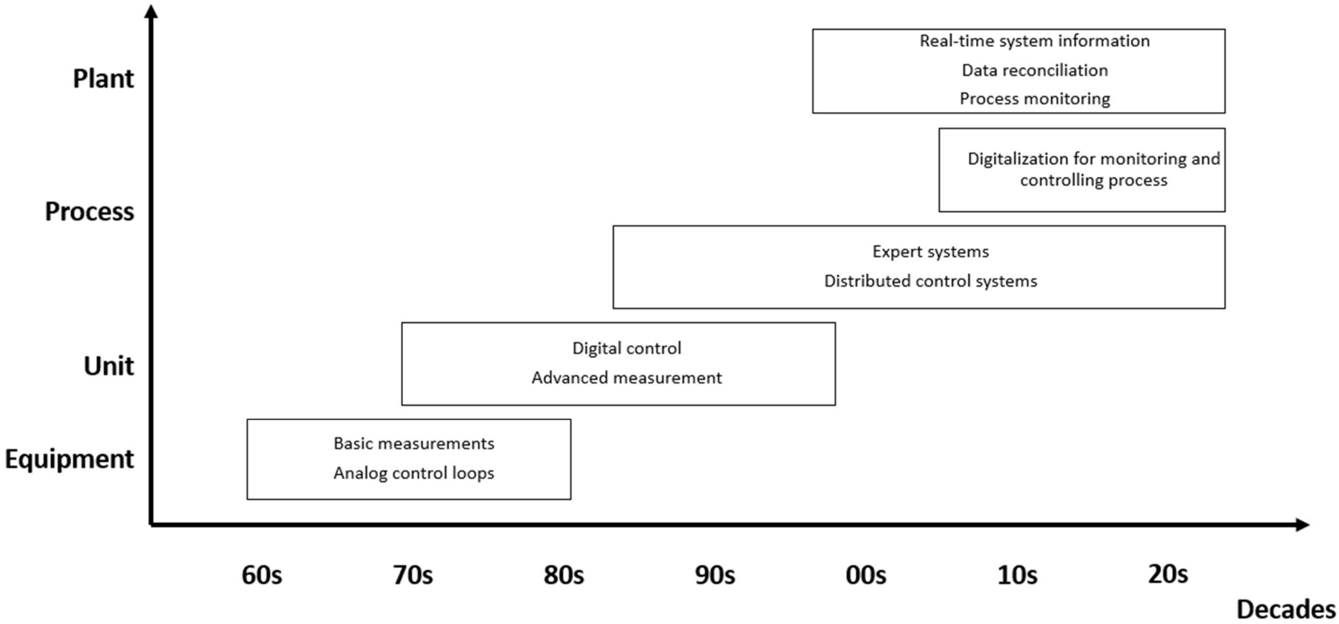

Figure 1. Automation system evolution in mineral processing based on Sbárbaro et al. [15] and Nad et al. [16].

The evolution of artificial intelligence enables complicated and interpretative solutions in contrast to empirical model approximations, offering complex representation learning, non-linearity, feature extraction, flexibility, and scalability with continuous and end-to-end learning. Artificial intelligence can handle diverse inputs, ambiguity, and uncertainty, making it suitable for different processing languages and computer vision. However, to identify solutions, we must provide explicit, known, and well-defined conditions [17]. Continuous improvement in the mining industry has made it common to find an interconnected control hierarchy such as the one presented in Figure 2, where instrumentation plays a fundamental role in ensuring the proper functioning of the plant. The second sector is dedicated to maintaining control over key variables, as evidenced in flotation processes where variables such as pulp level, foam level, air injection, and pump speed are regulated using conventional proportional, integral, and derivative (PID) control methods [18].

Reaching the highest levels of the pyramid, where we can find advanced flotation control (AFC) and optimised flotation control (OFC), will directly depend on a satisfactory control of the lower levels, where the PID controls are insufficient for the total management of the processes. The AFC structure must possess the capability to effectively mitigate disturbances arising from various sources, such as feed flow or other external factors, in addition to considering dynamic situations such as the accumulation of matter and delay times for the calculation of performance parameters such as recovery and the grade of the mineral. OFC will always seek to maximise the economic performance of the process, associating it with the recovery and grade of the concentrates obtained [19].

Metallurgical facilities frequently use PID control techniques due to their versatility and ability to be adjusted to the optimal operating parameters, achieving a response that suits the process [20]. Nevertheless, the intricate nature of multivariate processes precludes the application of conventional control techniques. In contrast, advanced control endeavours to establish a mathematical model that accurately characterises the operational and phenomenological aspects of the process under control. This model is subsequently validated through simulation. Expert systems, fuzzy logic, and predictive control models, both linear and non-linear, are viable alternatives in the industrial sector. These approaches can be effectively blended into a cohesive solution known as the predictive control of the fuzzy model [21]. Ai et al. [22] propose a novel approach that aims to overcome these limitations by using deep learning features and offline conservative double Q-learning control as an option to minimise the PID limitations in dealing with complex and nonlinear systems. During the 1990s, statistical features were used to classify froth structures in flotation cells during mineral processes [23]. This method was further developed by Hadler et al. [24] and applied by Polaris. Mines enhanced productivity and plant performance in lead zinc concentration standardised operational practices and adjusted reagent dosages based on the accumulated error over time. Their approach involved utilising set-point adaptive optimisation, incorporating a feedforward neural network (FNN) soft sensor for online feed grade estimation and a long short-term memory network (LSTM) to track fixed dosage set-points [25]. The implementation of automation in various processes has significant benefits, including the mitigation of staff exposure to hazardous environments, prevention of equipment damage, optimisation of operational expenses, and preservation of product quality [26,27].

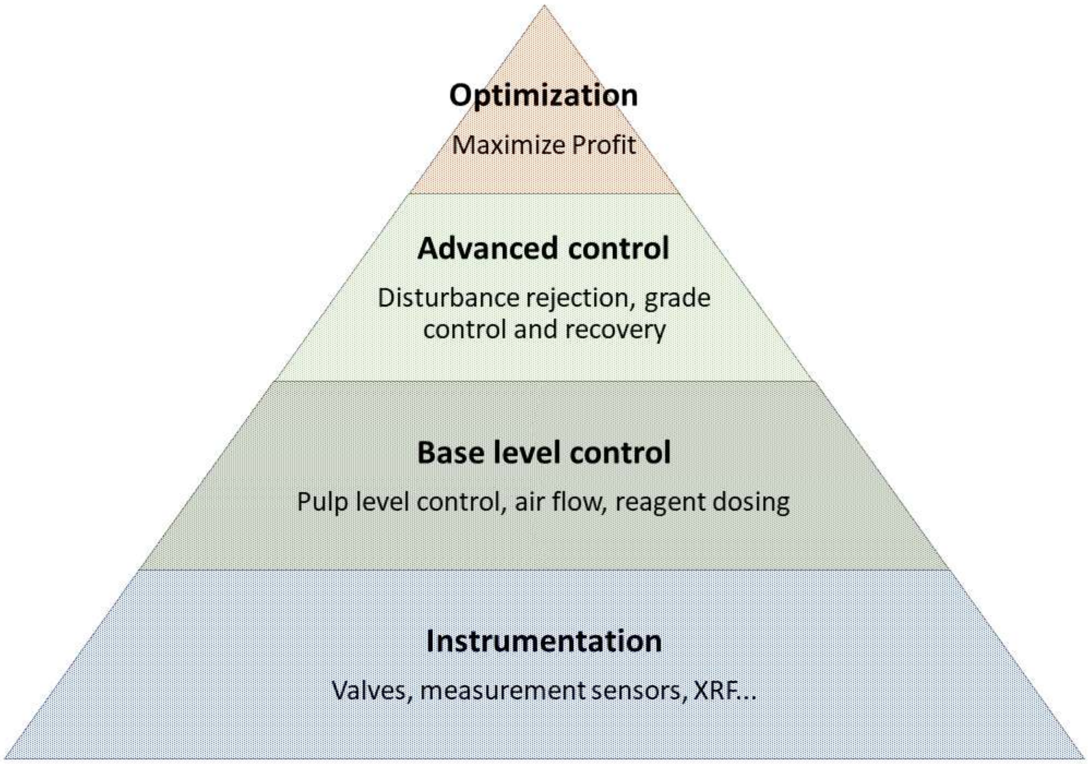

Figure 2. Level hierarchy for a flotation processes control system based on Shean et al. [18].

2.2. Application of Soft Computing in Mineral Extraction and Processing

The successful use of AI in the mining industry requires a collaborative effort among domain experts, data scientists, and technology vendors. To ensure the most appropriate AI solutions, each mining operation's individual demands and challenges must be carefully assessed. Concerns such as data security, staff retraining, and ethical considerations should also be addressed as part of the deployment approach. Through the analysis of mineral beneficiation and metal extraction processes, it is possible to identify some examples of the difficulty in controlling these processes optimally due to the instability of the variables involved. The composition of the slags impacts the recovery of the element of interest in pyrometallurgical processes such as the fusion process and is thus a variable that must be considered to obtain optimal recovery. However, because there are a variety of chemical reactions driving the process, it is difficult to describe a relationship between the compositions of the slags and the contents of components of interest that are present [28]. In the mineral processing field, Estrada et al. [29] investigated problems related to the flotation process such as the control of mineral granulometric sensitivity from the milling stage and milling global energy optimisation, as well as tailings transportation and deposition.

Martin et al. [30] analysed possible scenarios in which deposit destabilisation can occur, causing serious environmental and safety damage.

The study conducted by Fu et al. [31] examines the influence of several factors, such as mineralogy and viscosity, on thermodynamic changes and the manipulation of variables within kinetic models. Additionally, the application of soft computing has had a significant influence both in the areas of classification and concentration of minerals and in pyrometallurgy. Most of the applications are in artificial vision, probably due to the impulse to find methods to measure parameters such as particle sizes or chemical composition using image-based methods as a cheaper and faster alternative to techniques based on sample analysis [32]. The heap leaching process is an important part of the hydrometallurgical production line because it makes it easier to obtain the desired mineral. This process involves several control variables, including the properties of the leaching agent and the characteristics of the ore to be leached, such as its porosity, mineralogy, grade, and impurities, among others [33].

In this investigation, we have been able to analyse how the use of different soft computing tools has been incorporated in different stages related to mineral extraction and how they have been applied in situations related to both production and security, establishing the contribution and support needed to optimise mineral processes. A comprehensive analysis has been conducted on a total of 46 research publications that investigate the utilisation of soft computing techniques in various domains, including deposit operations, comminution, flotation, hydrometallurgical processes, and pyrometallurgical processes.

Table 1 presents a classification of the methods applied for each revised publication according to the applied area, and in Figure 3, the percentage of each methodology applied to the areas of interest is established, where for metallurgical processes, the artificial neural network (ANN) and model predictive control (MPC) are the most widely implemented. The relevance of identifying the variables with the greatest impact according to the associated operation has also been evidenced. The results obtained will be analysed in addition to the variables used to establish a comparison between the different methods and how their implementation has been approached. As shown in Figure 4, the areas of flotation and pyrometallurgical processes are those where the most studies have been developed, especially in the search for operational improvements for process control and prediction. This situation is directly explained by the possibility of accessing data available from existing monitoring in industrial processes, as will be seen later, and by the fact that these stages are the ones that present the greatest diversity of variable monitoring.

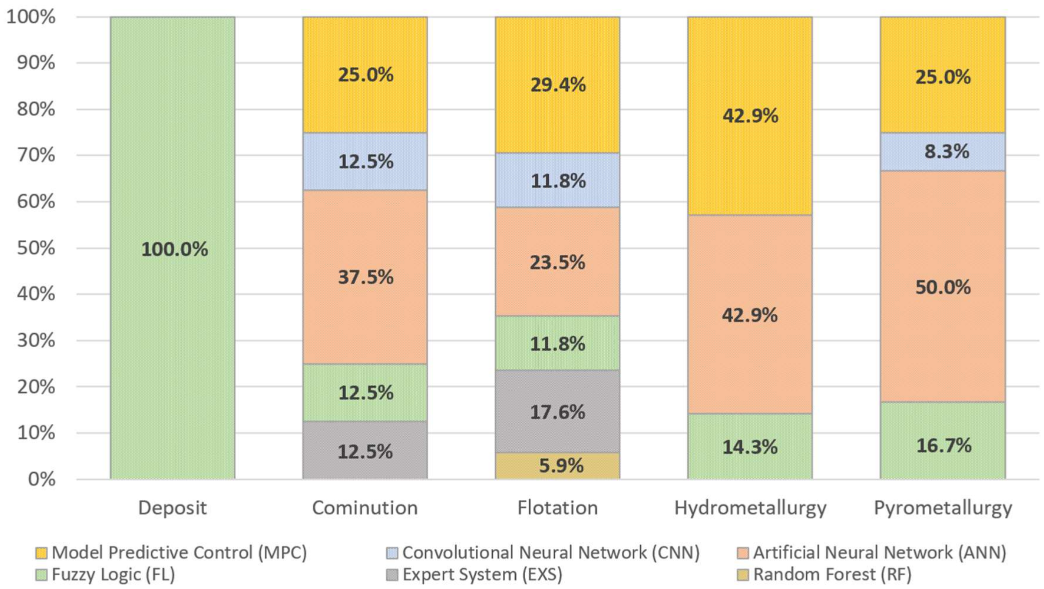

Figure 3. Comparison of soft computing methods applied in mineral extraction and processing.

Table 1. Summary of representative studies of soft computing application in mineral extraction and processing.

Author	Operation	Soft Computing Application RF	EXS	FL	ANN	CNN	MPC
Sun et al. [34]	Mining Stage			•			
Danish et al. [35]				•			
Li et al. [36]				•			
Stange et al. [37]	Comminution		•		•		
Tessier et al. [38]			•				
Olivier et al. [39]							•
Estrada et al. [29]							•
Hamzeloo et al. [40]					•		
Umucu et al. [41]					•		
Cai et al. [42]				•			
Olivier et al. [43]						•	
Aldrich et al. [23]	Flotation					•	
Moolman et al. [44]					•		
Ramasamy et al. [45]							•
Chen et al. [46]							•
Cortes et al. [47]							•
Aldrich et al. [48]						•	
Riquelme et al. [49]							•
Brooks et al. [21]							•
Ali et al. [50]		•		•	•		
Hoseinian et al. [51]					•		
Shean et al. [52]			•				
Zhang et al. [53]			•				
Ai et al. [25]				•			
Fu, Y. et al. [31]			•				
Ai et al. [22]					•		
Zhang et al. [54]					•		
Komulainen et al. [55]	Hydrometallurgy						•
Moreno et al. [55]							•
Pang et al. [56]				•			
Azizi et al. [57]					•		
Hoseinian et al. [33]					•		
Gao et al. [58]							•
Xu et al. [59]					•		
Gui et al. [60]	Pyrometallurgy			•			
Deng et al. [61]				•			
D. Liu et al. [28]					•		
J. Liu et al. [62]							•
Savic et al. [63]					•		
Ghea Puspita et al. [64]					•		
Cardoso et al. [65]					•		
Qian et al. [66]					•		
Cardoso et al. [67]							•
Wang et al. [68]							•
Yang et al. [69]						•	
Zhao et al. [70]					•		

RF: Random forest, EXS: expert system, FL: fuzzy logic, ANN: artificial neural network, CNN: convolutional neural network, MPC: model predictive control.

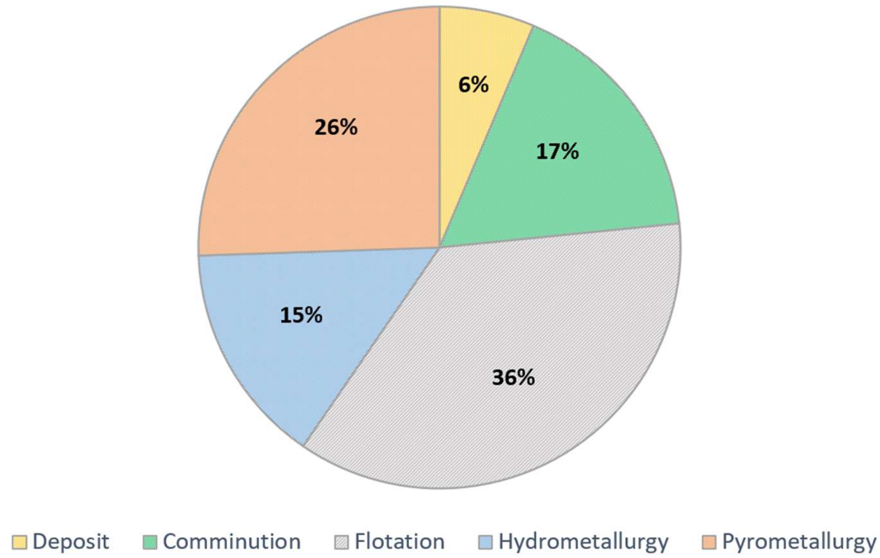

Figure 4. Soft computing application by mineral extraction and processing.

2.3. Applications of Soft Computing in the Mining Stage

Ongoing research and development efforts are being conducted within the mining industry to enhance safety measures and decision-making processes, employing techniques such as fuzzy logic and other methodologies (Table 2). Danish et al. [35] used fuzzy logic to predict mine fires in underground coal mines, while Li et al. [36] proposed a method to minimise the risk of gas explosion accidents in coal mines using fuzzy comprehensive evaluation. Similarly, Sun et al. [34] presented a fuzzy logic-based approach for predicting the risk of rock burst accidents in coal mines. It is possible to identify CO, O_2, N_2, and temperature as common variables in the application of fuzzy logic to the prediction and control of security mine conditions linked to variables that can be monitored in the field. With this understanding of which variables are most important for a given application, they can focus their efforts on collecting relevant data and refining their models accordingly. These studies provide evidence of the possible advantages that can be gained by employing soft computing techniques to enhance safety and decision-making procedures in ore deposit operations. From the studies applied to the mining stage, the most relevant variables that have been identified include:

(a) Density: For ore deposits, density is an important variable that provides information about the composition and mineralogy of the deposit.
(b) Water transmitting ability: Refers to the capacity of a rock or mineral to allow the flow of water through it. It is an important variable in understanding the material's hydrogeological characteristics.
(c) Fracture development degree: Corresponds to the extent and intensity of fractures or cracks within the rock or mineral. It can affect the permeability and fluid flow within the deposit.
(d) Confined water pressure: Refers to the pressure exerted by water within confined spaces or pores in the deposit. It can influence the stability and behaviour of the deposit.
(e) Watery property of the floor aquifer: This variable refers to the characteristics of the water present, such as its chemical composition, pH, and mineral content. It can impact the interaction between the aquifer and the ore deposit.
(f) Aquifuge thickness and strength: Refers to the thickness of impermeable or low-permeability layers that prevent the flow of water. Strength refers to the resistance of these layers to deformation or failure. These variables can affect the hydrogeological conditions and water movement within the deposit.
(g) Mining thickness and depth: This variable refers to the thickness of the ore body being extracted. Depth refers to the vertical distance from the surface to the ore

body. These variables are important in determining the feasibility and logistics of mining operations.

(h) Inclined productivity: Refers to the efficiency and productivity of mining operations in inclined or sloping deposits. It considers factors such as the angle of the deposit and the methods used for extraction.

Table 2. Characteristics of studies applied in the mining stage.

Paper	Problematic	Method	Data Used	Specific Variables	Results
Sun et al. [34]	Risk assessment of floor water inrush in deep mining	Improved fuzzy comprehensive evaluation, Delphi method, and analytic hierarchy process	Hydrogeological data from six industrial mining faces	Density, water-transmitting ability, fracture development degree, confined water pressure, watery property of the floor aquifer, aquifuge thickness and strength, mining thickness and depth, inclined length	The approach provides a tool for the risk assessment of floor water inrush in deep mining, where the results are consistent with the field-observed results.
Danish et al. [35]	Predicting mine fires in underground coal mines	Fuzzy logic model with Mamdani inference system	Data from 10 gas monitoring stations collected from sensors in an underground coal mine	Input variables: CO, O_2, N_2, temperature; Output variable: Fire intensity	The fuzzy logic system is reliable for decision making regarding fire intensity and assessing fire intensity with variables at the same time (validated using Graham's index), and identified suspected areas for spontaneous combustion.
Li et al. [36]	Quantitative risk assessment of gas explosions in underground coal mines	Combination of fuzzy analytic hierarchy process (FAHP) and Bayesian network (BN)	EXS application of risk factors related to gas explosions in underground coal mines	Flow rate, pressure, pipe diameter, pipe roughness coefficient, pump efficiency, energy consumption, cost	Inference to predict the probability of gas explosion risks with the determination of accident causes. The identification of the weight variables helps determine the optimal combination for flow rate, pressures, pipe diameter for each pipe segment, pump efficiency, and pipe roughness coefficient.

We can say that the soft computing application for the analysed studies is established, considering the following characteristics: 1. Risk factors: This is a key issue in assessing the risk of accidents in mines. The specific risk factors may vary depending on the study but generally include factors such as gas levels, ventilation failure, and water inrush. 2. Specific methods: Fuzzy logic and AHP: The application of fuzzy logic helps to handle uncertainty and imprecision in data under this variable selection. The analytical hierarchy process (AHP) determines the weights of different factors in a decision-making process, including the risk factors selected to be analysed in this quantitative risk assessment of gas explosions in underground mines.

2.4. Applications of Soft Computing in the Comminution Stage

The primary aim of comminution plants is to achieve the optimal particle size for efficient extraction of the desired mineral while also ensuring cost-effectiveness. However, to dissociate the low-grade minerals, the material must be finely ground, which implies high energy consumption in the milling area [54]. The grinding circuits are difficult to control due to poor plant models, external disturbances, and process variables that are not easy to measure [39]. In addition, the variables and properties of the extracted mineral, such as size, composition, and hardness, affect mill performance [38]. The disturbances in the operational conditions in milling directly affect the subsequent stages, such as leaching and flotation, that depend on the product obtained in this first stage, affecting the performance of a mining plant in general.

The strategies for reducing energy consumption in the mining industry have been extensively considered in recent years due to the increase in energy prices [71,72]. Therefore, control strategies in mining processes are one of the many ways to optimise this consumption, especially if the strategies consider global optimisation and ensure the stability of the system. The milling of minerals represents up to 50% of the energy consumption in a mineral concentrator plant. For this reason, Estrada et al. [29] developed a centralised hybrid model predictive control scheme (HMPC) in the grinding process that seeks to minimise specific energy consumption of the equipment and stabilise the feeding to the plant by ensuring an output particle size of 230 μm (65 mesh). With this hybrid model, the implementation of conventional strategies is a low-cost opportunity based, for example, on expert systems that handle variables and discrete events, and applying HMPC strategies allows the inclusion of discrete events in both the model and the controller. Stange [37] examines the application of ANN to the control of grinding circuits, specifically autogenous milling. Tessier et al. [38] describe a machine vision strategy for online rock mixture composition estimation, obtaining an overall accuracy of 92.5% for dry ore combinations.

In a run-of-mine ore milling circuit, Olivier et al. [39] propose using disturbance observers, specifically a fractional order disturbance observer (FO-DOB) and a Bode ideal cut-off disturbance observer (BICO-DOB), in conjunction with a standard PI controller to improve control performance in the presence of strong external disturbances and severe model–plant mismatches. Estrada et al. [29] use an industrial data-tuned grinding simulator to provide a hybrid model predictive control technique for mineral grinding circuits. Hamzeloo et al. [40] investigate the use of image analysis and neural networks to estimate particle size distribution on an industrial conveyor belt in a copper concentrator, attaining an overall RMSE of 6.11%. Umucu et al. [41] examine the application of ANN in modelling a calcite grinding system in mineral processing. Cai et al. [42] offer an approach for underground coal mining rock burst predictions utilising micro-seismic monitoring and a fuzzy comprehensive evaluation model. Olivier et al. [43] discuss the use of deep CNN to classify feed ore images into one of four categories based on size distribution, with an overall accuracy of 96.4%. Table 3 presents a comprehensive summary of the findings derived from each individual investigation. Based on the nature of the applications conducted in the studies, it is possible to categorise the studies conducted by Stange [37] and Tessier et al. [38] as utilising machine vision and image analysis techniques for diverse applications, such as estimating rock mixture composition, monitoring flotation froth, and analysing fragmentation.

Stange [37], Umucu et al. [41], and Hamzeloo et al. [40] applied ANNs for the control and modelling of mineral processing systems, as well as for classifying feed ore images based on size distribution. Olivier et al. [43] study the possibility of obtaining a convolutional neural network (CNN) model for characterising the size distribution of feed ore in run-of-mine ore milling circuits. Cai et al. [42] propose a methodology for rock burst forecasting in underground coal mining using microseismic monitoring and a fuzzy comprehensive evaluation model.

Table 3. Characteristics of studies applied in mineral comminution processes.

Paper	Problematic	Method	Data Used	Specific Variables	Numeric Results
Stange et al. [37]	Control of grinding circuits, specifically autogenous milling	ANN for control strategies and exploration of various control approaches by EXS	No specific data mentioned; theoretical discussion of ANN use in grinding circuit control	No specific variables mentioned; exploration of various control approaches using ANNs	Proposes two control strategies using ANNs for the control of autogenous grinding circuits. ANNs have significant potential in developing a model of the hydrocyclone classifier.
Tessier et al. [38]	Online estimation of rock composition for nickel mineral treatment	Machine vision approach for feature extraction, dimensionality reduction, and class boundary establishment using support vector machines	Digital images of five different mineral types and mixtures of them	Composition of rock mixtures: colour and textural features extracted from sub-images	Good estimation for mixture compositions for dry ore but some inaccuracies for wet ore mixtures due to light reflection. The proposed approach can be used for real-time monitoring of variations in run-of-mine ore composition.
Olivier et al. [39]	Improving control performance in a milling circuit	MPC controller with a fractional order disturbance observer (FO-DOB) and a Bode ideal cut-off disturbance observer (BICO-DOB)	Simulation data generated from a non-linear MIMO plant model	Controlled variables: product particle size, fraction of the mill volume filled with material, slurry volume in the sump. Mill-manipulated variables: solid feed-rate, water feed-rate, steel balls feed-rate, water flowrate into the sump and slurry flowrate into the cyclone	The FO-DOB and BICO-DOB are useful tools for ROM ore milling circuit control. This addition to the normal PI controller gives better results than the PI controller alone because of the decrease in the ISE values. The BICO-DOB has poorer disturbance rejection performance than the other two DOB varieties but gives the best set-point tracking performance.
Estrada et al. [29]	Develop an HMPC strategy for grinding circuits	Hybrid MPC controller identification procedure for two controlled variables	Data from industrial data-tuned grinding simulator	Conveyor feed rate, water feeding sump, SAG mill speed, product hardness, specific energy consumption, product particle size; Activation/deactivation of secondary grinding circuits and product granulometric distribution	A hybrid identification procedure for two controlled variables is correctly performed, with energy consumption minimization and the maintenance of particle size output.

Table 3. *Cont.*

Paper	Problematic	Method	Data Used	Specific Variables	Numeric Results
Hamzeloo et al. [40]	Estimate particle size distribution on an industrial conveyor belt in a copper concentrator	Image analysis and ANN	Images collected from an industrial conveyor belt in the crushing circuit of a copper concentrator	Particle size distribution, image pixel values, scaling factors, size features, eigenvectors and eigenvalues, cumulative passing %, volume of particles, metal ball diameter	Model estimations of particle size distribution achieve an overall RMSE of 6.11%. For area-based size estimations, the model obtains an RMSE of 4.45%. It obtains an RMSE of 18.54% for weight-based size estimations. Other size measures had RMSE values ranging from 5.45% to 37.11% for area-based size estimations and from 18.54% to 37.11% for weight-based size.
Umucu et al. [41]	Grinding system modelling of calcite in mineral processing	ANN–MLPNN and RBFNN	Experimental data collected from laboratory conditions	Input variables: cumulative percentages of ball mill feed, ball mill conditions, and grinding time. Output variables: ball mill product cumulative percentages	The RBFNN model performs better than the MLPNN model, highlighting the importance of analysing data and using capable systems for fast decision-making. The study used different powder filling levels for the calcite sample to evaluate the statistical data obtained from the ANN models.
Cai et al. [42]	Rock burst forecasting in underground coal mining	Fuzzy comprehensive evaluation model	Microseismic monitoring data from a coal mine and laboratory acoustic emission measurements of coal samples	Fault total area, space-time diffusivity, equivalent energy magnitude, seismicity degree, time information entropy, source concentration degree, seismic diffusivity	Importantly, the proposed methodology was successfully applied to a coal mine using a combination of indices for more accurate forecasting. Microseismic monitoring is a powerful tool for rock burst forecasting
Olivier et al. [43]	Characterization of the feed ore size distribution in a milling circuit	Deep CNN application for classification	Feed ore images captured from an industrial conveyor belt with a vertically mounted camera	223 images captured and categorised in four groups	The CNN achieved an overall accuracy of 96.4% in classifying into one of four categories based on size distribution, with an overall F1-score metric of 0.97.

Finally, Olivier et al. [39] and Estrada et al. [29] propose new control strategies for mineral grinding circuits, using techniques such as disturbance observers and model predictive control.

From the studies applied to mineral comminution processes, the most relevant variables that have been identified include:

(a) Particle size: A critical variable in comminution processes, as it affects the efficiency of subsequent mineral extraction stages. Achieving the optimal particle size is essential for efficient extraction of the desired mineral.
(b) Composition and hardness: The composition and hardness of the mineral being processed can significantly impact mill performance. Different minerals may require different grinding conditions to achieve the desired particle size.
(c) Operational conditions: Factors such as the mill speed, feed rate, and grinding media size can influence the efficiency and effectiveness of comminution processes.
(d) External disturbances: Changes in ore feed characteristics or variations in power supply can affect the stability and performance of comminution circuits.
(e) Product size setpoint: This variable is the target size for the final product and is used as a control parameter in grinding circuits.
(f) Rock types: These refer to different types of rocks or minerals present in the ore mixture. They are used as labels or classes for classification purposes.

2.5. Applications of Soft Computing in the Flotation Stage

The mineral flotation process is a complex dynamic process to control that cannot be optimised using constant control strategies because each mineral exhibits different behaviours before this process [73] and the mineral grade from the deposit is in constant decline, for example, reaching 0.4% in the case of copper [74]. This means that more controlled processes are required to maximise the separation of the species of interest from those without economic value that contaminate the final product. Keeping mineral flotation processes under control is a complex task since their stability depends largely on various variables such as the processed tonnage, mineralogy, percentage of solids, reagent dosage, and granulometry, among others (Table 4).

A change in these generates disturbances in the flotation process, which are reflected in the recovery results [18]. Historically, the optimisation of recovery results was achieved with experienced and qualified operators, but as Laurila et al. [75] explain, the flotation process is currently undergoing a paradigm shift towards automated control, ushering in a new era where:

- The design of flotation circuits is being simplified, which facilitates the regulation and control of the processes [76].
- The cell size has increased over time, going from 50 m^3 to designs close to 600 m^3 [77].
- The development of new technologies for online image analysis has made it possible to provide information on the status of the equipment involved in the process, such as stirring motors, valves, sensors, and pumps, and the quality of variable measurements such as air supply, pH, and bubble size [78].

The evolution of the soft computing application in processes linked to flotation processes has undergone evolutionary development, encompassing diverse techniques and technologies for monitoring and control, highlighting the importance of accurate data and control strategies in achieving optimal performance. When analysing the studies according to the applied methodology, Chen et al. [46], Cortés et al. [47], and Brooks et al. [21] analysed the implementation of advanced control strategies in mineral processing, specifically in ball mill grinding circuits and rougher flotation circuits, and the implementation of advanced technologies, including image processing, X-ray fluorescence, and diffused reflective spectroscopy, to optimise a copper roughing circuit. The publications cover topics such as MPC, hybrid ANN models, and multivariable predictive control systems, where the results show improved process stability, increased copper recovery, and significant performance improvements compared to previous control methods.

Table 4. Characteristics of studies applied in mineral flotation processes.

Paper	Problematic	Method	Data Used	Variables	Results
Aldrich et al. [23]	Classification of different froth structures in flotation cells	Decision tree and CNN algorithms for constructing knowledge-based systems	Surface froth images of two industrial flotation cells. Training data set consisting of 400 exemplars randomly sampled from the four classes	Froth image characteristics (e.g., statistical features)	The CNN system correctly classified unknown froth forms. The system improves profitability and reduces operating instability. The net classified froth structures with 96% accuracy, but limited training data sets reduced classification performance to 68%.
Moolman et al. [44]	Grinding efficiency of dry ball mills	Machine vision application to the feed with a ANN model from a laboratory-scale ball mill	Grinding aids and stage efficiency	Grinding data as particle size distribution, specific surface area, and grinding efficiency	SGLDM and NGLDM analysis of digitised froth images shows feature extraction potential. Neural networks classify foam shapes well. Dry ball mills can grind 25% better with grinding aids. SGLDM outperformed NGLDM at 66.7% with a 90% classification rate. However, NGLDM classified froth conditions better than SGLDM features at 78.9% compared to 52.4%.
Ramasamy et al. [45]	Comparison of predictive control schemes with detuned multi-loop PI controllers for controlling ball mill grinding circuits	MPC	Experiments conducted under five different operating conditions. Process model parameters such as the breakage rate function and hydrocyclone model parameters based on steady-state data collected from the circuit	Variables controlled: cyclone overflow fraction passing 104 µm and mill throughput. Fresh feed rate (0.375 to 0.5 kg/min), sump water addition rate, mill solids (67% to 74%), slurry pumping rate, hydrocyclone model parameters, breakage rate function, and sump level	Detuned multi-loop PI controllers oscillated and could not eliminate control loop interactions. The MPC system reached setpoints without overshoot or offset and decoupled well. Constrained MPC suppresses big input moves and is more resistant to operational conditions than PI controllers. PI controllers modify variables more than MPC. The mill throughput–sump water loop with PI controls is slower.

Table 4. *Cont.*

Paper	Problematic	Method	Data Used	Variables	Results
Chen et al. [46]	Implementing a model predictive control in a ball mill grinding circuit	MPC	Ball mill grinding circuit in an iron ore concentrator plant process variable	Particle size, mill solids concentration, sump level, circulating load, fresh feed rate, mill feed water flow rate, dilution water flow rate, vibratory conveyor speed, mill feed water control valve's opening, dilution water control valve's opening, pump speed	The study shows that MPC improves grinding circuit performance, ensures operational stability, and greatly reduces overload situation warnings. MPC lowered overload condition warnings by 31.9% over PID controllers. In addition, MPC lowered overload condition warnings by 85.8%. The MPC technique showed its efficacy in the invested time period, reducing alarms and ensuring operational continuity.
Cortes et al. [47]	Stabilise rougher flotation circuit operation	MPC application based in Honeywell's Profit Controller	Rougher flotation circuit data from Concentrator A-1 at División Codelco Norte	Airflow rate set points, level control, pH, and tonnage variation	Profit FLOT enhanced control and improved process stability and copper recovery. Profit FLOT on daily shifts increased the A-1 concentrator recovery by 1.5%. Higher-profit FLOT use, practise enhancements, strategy revisions, and operator training can still capture marginal benefits. Performance and recovery rates may improve further with further optimisation.
Aldrich et al. [48]	Control in froth flotation processes	Implementation of automated systems based on CNN using machine vision	Froth images obtained from laboratory and industrial flotation cells, operational data such as the air flow rate, pulp level, and concentrate grade	Bubble size and shape, air flow rate, pulp level, concentrate grade	Machine vision and image analysis techniques can be used to monitor froth stability, but fully automated control is not possible.
Riquelme et al. [49]	Identify and measure bubble size distribution in flotation	Image processing and a parametric method with a circular Hough transform (CHT) and log-normal distribution for MPC	Bubble images from flotation columns obtained through a camera system conducted with different frother concentrations and superficial air velocities	Frother concentration, superficial air velocity, bubble size distribution parameters, bubble Sauter mean diameter, flotation recovery	CHT detects clustered bubbles better than other approaches. Log-normal distribution estimates BSD well. BSD parameter dynamics are explained well by the non-linear Wiener model. After experiments, static models were estimated using a non-linear least squares technique with R2 = 93.3% and 98.5%.

Table 4. *Cont.*

Paper	Problematic	Method	Data Used	Variables	Results
Brooks et al. [21]	Optimization of a copper roughing circuit to improve recovery in an oxide rougher circuit	Application of sophisticated technologies such as image processing, X-ray fluorescence, diffused reflective spectroscopy, and cascaded MPC	Manipulated, disturbance and controlled variables in flotation cells	Feed flows, densities, air flows, pulp levels, feed, concentrate and tail Cu grades, and froth velocity	Successful MPC installation improves float and Cu recovery. Innovative measurement technology improved the accuracy and reliability of critical control parameters such as the Cu grade, froth velocity, and concentrate and tail grades.
Ali et al. [50]	Predict the flotation behaviour of fine high-ash coal in the presence of a hybrid ash depressant	Random forest, ANN, fuzzy logic, and adaptive neuro-fuzzy inference system	Flotation experiments on fine high-ash coal with a training data set (80% of total data) and test dataset (20% of total data) containing five inputs and two outputs	Inputs: Al-PAM polymer dosage, pH, polymer conditioning time, dispersant dosage, and impeller speed. Outputs: combustible recovery and froth ash content	The models predict the performance of the coal flotation process. The fuzzy logic model had the best prediction performance in coal flotation. Overall accuracy: FL > ANN > ANFIS > RF > HyFIS.
Hoseinian et al. [51]	Develop a model to predict SAG mill power	Hybrid ANN algorithm model application	SAG mill operation dataset from Aq Darreh gold processing plant (GA population size: 100, max generation: 450)	Feed moisture, mass flowrate, mill load cell mass, SAG mill solid percentage, inlet water flow rate, outlet water flow rate, work index, and mill power	Correlation coefficient (R) of the GANN model: 0.9127 in testing compared to ANN alone with an R of 0.7947. Obtained relationship input parameters for the work index, inlet and oulet water to the SAG mill, mill load cell mass, SAG mill solid percentage, mass flowrate and feed moisture. Mean squared error (MSE) of the GANN model: 0.0451 in training, 0.0430 in testing. MSE of the ANN model: 0.1549 in training, 0.4054 in testing
Shean et al. [52]	Predicting changes in pulp height in froth flotation	Development of a dynamic model from a flotation laboratory test	Froth flotation mass balance and calibration using experimental data	Bubble size distribution, air flow rate, and pulp height under different conditions	The dynamic model predicts steady-state froth flotation pulp height variations. The experimental system responds slower to the reagent than the model because the model assumes the system is well mixed, while the experimental results show plug flow. The model can be adjusted to reflect industrial flotation control's dynamic nature.

Table 4. *Cont.*

Paper	Problematic	Method	Data Used	Variables	Results
Zhang et al. [53]	Simulating the relationship between the reagent dosage and froth surface appearance in a lead–zinc flotation plant	Hammerstein–Wiener-based model with the illumination modelling-based marker watershed method for EXS application	Reagent data and froth surface images collected from a lead–zinc flotation plant (149 pairs used for developing the Hammerstein–Wiener model and 60 pairs used for testing and validating the model)	Reagent variables (frother, activator, and collector dosage), froth surface variables (bubble size distribution, froth surface image, and highlight spot marker), model variables (Hammerstein–Wiener model)	The log-normal distribution can describe lead–zinc flotation plant bubble size distribution (BSD) in the quiet zone below the interface. The Hammerstein–Wiener model beats the Wiener model, LS-SVM model, and neural network model in fitting accuracy and performance with an RMSE of 0.0420 and an R-squared of 0.9721. The proposed approach can guide reagent dosage changes to manage mineral processing froth flotation and segment zinc froth image bubbles with 95.6% accuracy.
Ai et al. [25]	Flotation reagent control	Reduction in extracted deep learning features using a stacked autoencoder, fuzzy association setpoint calculation, and offline Q-learning-based reagent control	Feed characteristics, froth grade, flotation reagents, and froth videos. RL benchmark environment data with 1,000,000 samples using a soft actor–critic (SAC) controller	Froth images to extract four features: bubble size, bubble shape, froth velocity, and froth color.	The method outperformed other existing methods in terms of the MAE and qualified ratio of the concentrate grade. It was effective and promising for practical flotation reagent control.
Fu et al. [31]	Effect of particle size and process time on magnesite flotation using machine learning to predict flotation performance	EXS application and mathematical modelling	Flotation experiments performed on magnesite with seven size fractions and six flotation times	Feed particle size, flotation time, pulp pH, collector dosage, recovery rate of MgO and SiO_2	Optimal particle size range identified for magnesite flotation of 30 to 48 μm. The EXS method performs better than other models in predicting the MgO and SiO_2 recovery, which increased from 54.18% to 95.12% and from 50 to 400 mg/L, respectively. The SC model is an effective tool for predicting the effects of flotation parameters.

Table 4. *Cont.*

Paper	Problematic	Method	Data Used	Variables	Results
Ai et al. [22]	Set-point adaptive optimization and control strategy for antimony flotation process	Fuzzy logic functions, machine vision, and FAR mining to extract information and generate optimal set-points	Feed grade, reagent dosages, froth image, and concentrate grade. A total of 1000 groups of data in the desired concentrate grade range, with 950 groups to generate FARs and the rest for validation	Feed grade, reagent dosages, froth image, concentrate grade, and image features: froth height, froth colour, froth velocity, and bubble size	Better performance compared to manual manipulation and other automatic control methods with an FNN-based prediction accuracy for feed grade of RRMSE: 2.94% and MRE: 8.73%. Improved control performance in concentrate grade.
Zhang et al. [54]	Develop an adaptive modelling method for froth flotation reagent control	An adaptive ANN auto-regressive model (A-NNARX) for dynamic froth flotation control. In a non-linear model, the model predicts the flotation reagent control technique	Flotation industry data. The data are categorised by feed grade: low zinc, normal, high zinc, and high lead	Concentrate quality, zinc and lead feed grade, froth videos, flotation reagents, hand-crafted image characteristics, bubble size distribution. Colour, texture, and foam velocity. PCA components (control inputs, process outputs), quadratic cost function, Euclidean distance (ED) between the target foam image features and control results, histogram bins, test samples, and training data	The A-NNARX model improved the qualified ratio by 0.1666 compared to manual control, achieved better performance in terms of Euclidean distance, and increased the qualified ratio under expert control from 0.7500 to 0.8194 while decreasing the MAE error by 0.1384. A weight-level regularization method improved the capacity for deformation evaluation.

Ai et al. [25] and Aldrich et al. [23] discuss various aspects of froth flotation in the mining industry, including control strategies, machine vision through image analysis, and machine learning techniques for classifying froth structures. Moolman et al. [44] and Zhang et al. [53] include the use of digital image processing techniques to extract features from froths, the development of models to simulate the relationship between the reagent dosage and froth surface appearance, and the use of machine vision and predictive modelling to control the process. The papers provide numeric results and highlight the potential for improved process control and optimisation in flotation plants. Ali et al. [50], Fu et al. [31], and Ai et al. [22] discuss the use of artificial intelligence models to predict the flotation behaviour of fine high-ash coal in the presence of a hybrid ash depressant, the effect of particle size and flotation time on magnesite flotation, a set-point adaptive optimisation for the antimony flotation process applying an ANN soft sensor to estimate the feed grade online, and a FAR-based set-point generator to adjust the set-points of the image features. Zhang et al. [54] research an adaptive modelling method for industrial processes specifically in the context of froth flotation reagent control. The method involves an incremental learning approach to update the process model and preserve performance on old patterns while accommodating new process “excitation” patterns. The adaptive process model is then used in a nonlinear predictive control strategy for flotation reagent control. Ai et al. [25] provide an approach that involves fuzzy association setpoint calculation and offline Q-learning-based reagent control in froth flotation processes, which can improve the efficiency and effectiveness of industrial processes. Finally, Shean et al. [52] present a dynamic model for predicting changes in pulp height in aerated slurry tanks in froth flotation specifically. The model is developed and validated through the use of experimental data, which includes measurements of bubble size distributions and air flow.

The findings can be categorised into two groups when evaluated in relation to the response variable: flotation process optimisation and bubble size distribution. Chen et al. [46], Ramasamy et al. [45], Cortés et al. [47], and Ali et al. [50] discuss the use of artificial intelligence and model predictive control to optimise and improve the efficiency of mineral processing and flotation processes. These studies demonstrate the potential of these technologies to improve process control and optimisation, leading to increased profitability. Riquelme et al. [49] present a new technique for identifying and measuring bubble size distribution (BSD) in flotation columns using image processing and a parametric method. The circular Hough transform (CHT) is used to detect bubbles in the images, and a log-normal distribution is used to estimate the BSD. A non-linear Wiener model is developed to explain the dynamic behaviour of the BSD parameters. The results show that the CHT method is superior to other methods in detecting clustered bubbles, and the estimated number of bubbles is similar to what is obtained with a visual inspection. Another study, similar to the one developed by Moolman et al. [44], seeks to establish patterns from digital image processing, specifically using the spatial grey level dependence matrix (SGLDM) and neighbouring grey level dependence matrix (NGLDM) methods, to extract features from digitised images of froths in a copper flotation plant. The extracted features can be used to identify various process phenomena in the plant and develop control strategies for flotation plants. The paper also discusses the significance of froth appearance in flotation processes and the potential for better control of a plant through a more accurate and systematic interpretation of the physical features of the froth phase. A neural network was used to classify different froth structures based on the extracted features, and the study demonstrated the potential of neural networks for pattern recognition in complex processes. If an analysis of the variables included in these investigations is conducted, it is feasible to establish certain considerations:

(a) Flotation performance variables: These include parameters such as float recovery, total copper recovery, acid-insoluble copper recovery, and concentrate and tail grades. These variables are used to evaluate the effectiveness of different control strategies and technologies in improving flotation performance.
(b) Speed rate: An important parameter in flotation circuits, as it affects the residence time of particles in the circuit and can impact flotation performance. Operator control and MPC velocity control show the impact of different control strategies.
(c) Bubble size and gas holdup: These variables are important in understanding the behaviour of froth flotation systems, as they impact froth stability, mass pull, and flotation performance. The relationship between the bubble size and air rate can be used to predict changes in the pulp height.
(d) Reagent dosage: Reagents are used in flotation circuits to promote particle–bubble attachment and improve flotation performance. A relationship exists between the reagent dosage and froth surface appearance, and machine vision and predictive modelling can be used to control reagent dosage.
(e) Advanced measurement technologies: The use of advanced measurement technologies, such as image processing, X-ray fluorescence, and diffused reflective spectroscopy, improves the measurement and control of key variables in mineral processing operations. These technologies enable the more accurate and reliable measurement of parameters such as the Cu grade, froth velocity, and concentrate and tail grades.

From the analysis, artificial intelligence models have shown promising results in predicting flotation behaviour and classifying froth structures. For example, Chen et al. [46] show that decision tree methods and artificial neural networks can distinguish between froth features that are difficult to discern with the naked eye, with an overall classification accuracy of approximately 92.5% for copper flotation froths and 96% for platinum flotation froths. Similarly, Ramasamy et al. [45] show that Mamdani fuzzy logic (MFL) models performed the best among all the models tested for predicting the performance of the coal flotation process, with R-squared values of 0.9483 and 0.9243 for the training and testing phases, respectively, when predicting the froth ash content. Advanced measurement technologies, such as image processing, X-ray fluorescence, and diffused reflective spectroscopy, have shown promise in improving the measurement and control of key variables in mineral processing operations. For example, Brooks et al. [21] discuss the implementation of advanced technologies, including image processing, X-ray fluorescence, diffused reflective spectroscopy, and cascaded model predictive control (MPC), to optimise a copper roughing circuit. The results show improved process stability and increased copper recovery compared to previous control methods.

Model predictive control (MPC) has shown promise in optimising mineral processing operations and improving plant performance. Zhang et al. [54] provide an adaptive modelling method for industrial processes with a focus on froth flotation reagent control. The method employs an incremental learning strategy to update the process model and maintain performance in existing patterns while tolerating new process “excitation” patterns. The adaptive process model is then applied to a nonlinear model of predictive control. Experiments based on historical data and in a real-world lead–zinc froth flotation plant show promising results for practical application. The reagents used in the flotation process aim to change the surface properties of the mineral with a certain degree of release [15], and the hydrophobic properties cause them to separate from each other; then, they are contained in the pulp and selectively adhere to bubbles [79]. The relationship between the foam structure that develops on the pulp surface and the efficacy of the flotation process, namely in terms of the mineral grade and recovery, has been established in previous research [48]. By analysing commonalities between the studies, it is possible to identify that the use of advanced technologies and control strategies can lead to significant improvements in plant performance, including increased total and insoluble Cu recovery. Advanced measurement technologies such as image processing, X-ray fluorescence, and diffused reflective spectroscopy can enable more accurate and reliable measurements of key control parameters, such as the Cu grade, froth velocity, and concentrate and tail grades. The application of machine learning and artificial intelligence models can be used to predict flotation behaviour and classify froth structures, leading to improved control and optimisation of flotation processes.

Model predictive control (MPC) approaches have the potential to enhance the precision of control in the roughing circuit, enhance the stability of the float bank, and increase the recovery and grade. Froth image analysis has the potential to significantly improve process control and optimisation in flotation plants, but further research is needed to assess the predictability of froth grade from froth image features. These antecedents indicate that the approach developed in the soft computing application focuses more on the optimisation and control of the variables of the processes or on the process itself, but not on the control of the foam of a flotation process, since its structure can reflect the floating behaviour, indicating both the grade and the recovery [48]. In the MPC, the control signal is minimised in such a way that its squared error is reduced at each instant of time. What makes this model attractive are its algorithms since they have the natural ability to consider imposed technological and process constants as input and output values [80]. An indispensable part of this model is the use of algorithms from a dynamic model to predict the output values of a system based on past and current values, as well as future control signals. The development of this principle is complex to address in industrial systems, requires a broad knowledge of the physicochemical phenomena involved, and includes the execution of information from experiments that is exhaustive and sufficient to identify the parameters that are key in the process [58]. On the other hand, an MPC can be constructed using historical data, making this type of model more convenient than kinetic models [81]. For example, an artificial neural network of two phases was established by Sun et al. [82], in which one phase is used to derive and create a nominal model of a flotation process based on categories that do not follow an intrinsic classification and a second phase is designated to prevail against discordance with the nominal model. To achieve finite time control for a class of non-linear systems in this second phase, a radial basis function was implemented to handle the saturation of input variables that could occur and thereby generate constant error traceability.

Authors such as Kallioinen et al. [83], Harbort et al. [84], and Carr et al. [85] identified that the sizes of the flotation cells would increase their volume, with the main benefits being a reduction in capital expenditure and operating costs, lower energy consumption per cubic metre, a lower amount of instrumentation, and facilitation of the control of each cell. The use of advanced control at this stage is of great interest due to its high performance in terms of predictability and data analysis in the representation of complex processes. With this, an advanced control strategy can be implemented to achieve adequate reagent control where the model can be updated as the base data acquires new monitoring data using a model predictive control strategy [86]. This will significantly impair the prediction performance when a dynamic model is used [87]. The adaptive model technique has the potential to solve this problem by maintaining the performance of old data and keeping the dynamic model updated with the new "excitation" patterns based on the new measured data [88]. Rosenfeld et al. [89] employed a methodology consisting of four steps: training, data tuning (finetuning), retraining, and incremental learning. This strategy involved the integration of data training and self-learning approaches.

Therefore, an incremental learning method is an interesting alternative which seeks to update industrial process models based on neural networks. Unlike traditional incremental learning, where the discrepancy or restriction between an original and updated model is measured by the "deformation" of all hidden networks, the deformation of the last hidden layer of the neural network is concentrated. Furthermore, a weight regularisation method is designed for the last hidden layer of the neural network to show the performance capacity through strain evaluations. Ultimately, the foam flotation process, which exhibits significant inconsistencies, is controlled by the implementation of predictive control procedures utilising an empirically derived model that is continuously updated in an incremental manner.

2.6. Applications of Soft Computing in the Hydrometallurgy Stage

In the context of hydrometallurgical processes, various techniques have been employed to enhance the efficiency and control of the process. Methods such as artificial neural networks and multiple linear regression, data-driven model predictive control, dynamic process simulators, and fuzzy parameter self-tuning PID control algorithms have been implemented in the process, which includes leaching, column leaching, and solvent extraction (Table 5). Azizi et al. [57] and Komulainen et al. [90] use mechanistic models to explain how copper moves from the watery phase to the organic phase during the extraction process. The first study places emphasis on modelling the settler hydrodynamics, while the second one presents a dynamic process simulator for copper solvent extraction plants using mixer–settlers. Both studies report good agreement between simulations and measurements, indicating that the mechanistic models accurately describe the process trends. Komulainen et al. [90] emphasise the importance of parameter adaptation for modelling accuracy, especially for efficiency parameters. Gao et al. [58] use ANN to predict gold recovery and thiourea (TU) consumption during the leaching process. The results show a high prediction accuracy for the trained model, with a minimum absolute error of gold recovery varying from 1.46% to 3.45% and a prediction accuracy between 94.46% and 98.06%. The absolute errors of TU consumption varied from 0.079 to 0.428 kg/t, and the accuracy of the predictions was between 95.15% and 99.20%. As previously stated, the variables selected for model generation are part of the regular monitoring that is carried out in operation, which includes observation of the copper concentration [57,58,90], temperature [57,58], leaching time [58,90], and pH [58,90].

Table 5. Characteristics of studies applied in mineral hydrometallurgical processes.

Paper	Problematic	Method	Data Used	Specific Variables	Results
Komulainen et al. [90]	Developing a dynamic process simulator for copper solvent extraction plants	Mechanistic models for MPC	One month of operating data from an industrial copper solvent extraction process	Input variables: PLS concentration, lean electrolyte concentration and rate, and flow rates. Output variables: Loaded and barren organic concentrations and rich electrolyte and raffinate concentrations	Mechanistic models accurately describe the SX process trends. The mean residual is well below 2% for organics and rich electrolyte and around 6% for raffinates, which is considered very good considering the poor measurement accuracy of these streams
Moreno et al. [55]	Developing a dynamic model for mixer–settler units used in the solvent extraction (SX) process of copper plants	Dynamic modelling for MPC	Copper concentration, pH, SX operation variables, equilibrium isotherm calculations, and mass transfer expressions	Input variables: Aqueous inlet flowrate, pH, Cu^{+2} aqueous and organic inlet, organic inlet flowrate, mixer volume, settler volume, and free acidity in electrolyte. Output variables: Volumes of phases in the mixer, flowrates at the mixer exit, Cu^{+2} in aqueous phase at the mixer exit, and Cu^{+2} in organic phase at the mixer exit	By incorporating time delay and flexible model fitting parameters, a better fitting settler model was found, accurately reproducing changes in SX. The relative mean squared errors for outlet copper concentrations in the extraction unit were 0.03% (aqueous phase) and 6.76% (organic phase), while for the stripping unit they were 0.07% (aqueous phase) and 2.89% (organic phase).
Pang et al. [56]	Improving control performance in leaching rare earths using a self-tuning PID control algorithm	Fuzzy parameter self-tuning PID control algorithm	Simulation data	pH and element contents in solution. Proportional, integration, and differential adjustment factors	Simulation results show that the fuzzy parameter self-tuning PID control algorithm outperforms traditional PID control algorithms in terms of control performance, response time, and accuracy. A relationship between the pH value and the amount of the initial solution is established

Table 5. *Cont.*

Paper	Problematic	Method	Data Used	Specific Variables	Results
Azizi et al. [57]	Predicting gold recovery in the cyanidation process	ANN and MLR	Cyanide leaching circuit of gold mine	Input includes pH, solid percentage, NaCN concentration, particle size and leaching time. Output: Au recovery	ANN provides efficient and cost-effective, with highly accurate predictions of 0.556 for the training and 0.67 compared to MLR. Leaching time and particle size are the most important factors affecting gold extraction.
Hoseinian et al. [33]	Optimization of the copper oxide column leaching process	ANN and GANN	A database of 120 sets of copper leaching column tests; 96 sets were used to train the network and 24 sets were used to test the model	Particle size, column height, leaching time, and acid flow rates	Copper recovery has an inverse relation with the column height and particle size and a direct relation with the leaching time and the acid flow rate. The GANN model is more efficient than the ANN model for Cu recovery prediction with reasonable accuracy. The algorithm can be incorporated in the training phase of a network to improve prediction.
Gao et al. [58]	Developing a data-driven model predictive control approach for dynamic systems	Data-driven MPC approach that combines modified partial least squares (PLS) and MPC	Multiple input and output variables from laboratory tests	Input variables: Input flows and heat to the tank. Output variables: Cooling water temperature, atmospheric temperature, steady state temperature, and steady state level	The proposed MPC approach has high prediction precision and an ability to cope with dynamics in the process, outperforming traditional MPC and MPC in a traditional PLS framework. This was tested on a continuous stirred tank heater system
Xu et al. [59]	Using thiourea as an alternative to cyanide for gold leaching from refractory ores	Grey relational analysis and artificial neural network models	Results of leaching experiments conducted on a high-arsenic gold concentrate using A. ferrooxidans and TU as a leaching agent	Leaching time, initial pH, temperature, TU dosage, stirring speed, and ferric iron concentration	GRA and ANN models can efficiently reflect practice and provide effective suggestions for controlling optimum parameters in the leaching process. The absolute errors of gold recovery varied by 2.5% and the accuracy of the predictions was around 96%. The accuracy of the other predictions was around 97%.

There are specific variables according to the reality of the process and operating conditions, including aqueous and organic phases [57,90], ferric iron concentrations [58], and settler hydrodynamics [57]. Based on existing studies, there is an efficient and cost-effective method [55] with high prediction accuracy and improved control performance using artificial neural networks (ANN) and genetic algorithm neural networks (GANN), as presented by Xu et al. [59]. For example, Hoseinian et al. [33] report that the GANN model is more efficient than the ANN model for predicting copper recovery in column leaching processes. Gao et al. [58] establish an ANN model to predict gold recovery and TU consumption with high prediction accuracy, and Pang et al. [56] demonstrate superior control performance, reaction time, and accuracy compared to the classic PID control algorithm.

From the studies applied to mineral hydrometallurgical processes, the most relevant variables that have been identified include:

(a) pH: This variable plays a significant role in controlling the behaviour of chemical reactions. It is an important variable in the leaching process as it can affect the rate of element recovery.
(b) Particle size: Refers to the size of the particles of the element of interest in the ore. It is an important factor that can affect the efficiency of the leaching process.
(c) Temperature: A key variable that affects the efficiency and kinetics of chemical reactions, directly affecting the rate of element recovery
(d) Time: Refers to the duration of processes such as leaching. It is a critical variable as it determines the amount of time available for the element of interest to dissolve into the leaching solution.
(e) Element of interest's grade: The grade or initial quantity of the element to recover is a relevant base variable considered in predicting models for copper and gold recovery. This variable can be complemented by the change in element concentration in solution during the process.
(f) Reactive consumption: Reagents are used to increase the kinetics of chemical reactions. Here, the consumption of thiourea or agents such as ferric ions can impact the recovery efficiency.
(g) Solid percentage: Corresponds to the proportion of solid material in a solution. It is a relevant parameter in solid–liquid processes such as stirring leaching that can influence the efficiency.
(h) Stirring speed: Refers to the speed at which the leaching solution is agitated. It is a parameter that can influence the contact between the particles of the element of interest and the leaching solution, affecting the recovery rate.

2.7. Applications of Soft Computing in the Pyrometallurgy Stages

In high-temperature metallurgical processes such as copper losses, slag monitoring, silicon content prediction, and matte grade optimisation, soft computing methods such as MPC, ANN, CNN, FL, dynamic modelling and simulation, hybrid intelligent models (combining fuzzy logic, neural networks, and other techniques), feature selection methods based on mutual information, genetic algorithms, and other techniques have been applied, improving the efficiency, productivity, and cost-effectiveness of metallurgical processes (Table 6). As previously mentioned, the slag compositions have a notable influence on the recovery of the element of interest, such as gold or copper. These methods are used to develop and validate models for predicting matte grade in the copper flash smelting process or hot metal quality in a blast furnace. The base variables identified in this type of process include temperature, pressure, chemical composition, flow rate, time, and pH. Some specific variables are used depending on the pyrometallurgical process being studied, such as the grade, element content, and slag basicity and volume. From the studies, it was identified that soft computing applications improve accuracy and efficiency in processes such as the prediction of steel quality or the optimisation of blast furnace ironmaking. Additionally, the importance of feature selection is highlighted in developing accurate models and the ways ensemble learning methods can better cope with complex variations in industrial processes compared to traditional machine learning methods.

Table 6. Characteristics of studies applied in mineral pyrometallurgical processes.

Paper	Problematic	Method	Data Used	Specific Variables	Results
Gui et al. [60]	Predicting matte grade in copper flash smelting	Integrating a multiphase and multi-component model with a fuzzy model	A total of 154 groups of industrial data collected from industrial production	Matte grade, copper concentrate content, pyrite content, S content, Fe content, SiO_2 content, CaO content, oxygen volume, blast volume	Higher prediction precision, stronger generalization ability, reduced mean square root error, and decreased training time.
Deng et al. [61]	Incremental learning approach for accurate system modelling	Dynamic fuzzy neural network (D-FL) using incremental learning algorithm (ILA)	Four datasets: Chaotic Mackey–Glass time series, Box–Jenkins gas furnace data, displacement prediction in the dam, and ionosphere delay prediction for the GPS satellite	Input variables: Air temperature, reservoir water level, and dam run time. Output variable: Displacement of point L3H291R. Other variables: Epoch number, times, residual error, MAPE, RMSE, and MAE	Good performance in modelling accuracy, learning convergence, and computation time.
D. Liu et al. [28]	Estimation of gold content in slag	ANN and nonlinear regression	Small-scale experiments using a specific slag composition system to simulate industrial processes for gold extraction	Independent variables: Compositions of the soda–borax–silica glass–salt slag system. Dependent variable: Gold content in slag	The ANN method produces better estimations of gold content with higher precision compared to the traditional regression method.
J. Liu et al. [62]	Predicting matte grade in the copper flash smelting process	MPC application based in dynamic mass balances with equilibrium relationships	Data collected at a copper smelter for 30 days	Matte grade, oxygen partial pressure, temperature, desulfurization ratio, Cu concentration, species mass balance (Cu, Fe, S, O_2, SiO_2, CaO, Al_2O_3, MgO), operational parameters, slag Cu losses, mechanical entrainment droplets of matte and dissolved Cu	The model is effective in providing guidance for controlling the copper flash smelting process with a maximum relative error of 3.3% and an average relative error of 0.54%. Regression equations for predicting the ratio of desulfurization and copper in slag were also presented.
Savic et al. [63]	Predicting copper losses in silicate slag from the sulphide concentrate smelting process	MLR analysis, ANN, and ANFIS	Industrial data from a sulphide copper concentrate smelting process	Input variables: The percentage of copper, iron, and silica in the concentrate, percentage of coke and flux in the charge, and oxygen amount in the process. Output variable: Cu content in silicate slag	The ANFIS approach was found to be the most accurate, with a coefficient of determination of 0.989 in the training stage and 0.719 in the testing stage.

Table 6. *Cont.*

Paper	Problematic	Method	Data Used	Specific Variables	Results
Ghea Puspita et al. [64]	Optimization of the reduction process of saprolite ore composites	ANN	Results of the reduction process of saprolite ore composites collected from extractive metallurgical laboratories	Ratio of coal (%), process temperature (°C), time duration (hours), composite type	An optimal factor combination for the reduction process is established by ANN (composite $SB_{15}Ca_{10}P_2$, 1200 °C and duration of 3 h). A validation of the results was possible through Fe, Al, and Si mass composition comparisons.
Cardoso et al. [65]	Predicting production and quality control of hot metal in a blast furnace	ANN model based on a committee machine	Data obtained from the operation of a blast furnace at an industrial steelmaker	Input variables: Fuel, air volume, temperature. Output variables: Iron oxide, coke	Developed an artificial neural network model with a general correlation of 91.1%.
Qian et al. [66]	Anomaly detection in a steelmaking process with multichannel profiles	Functional derivative MPC support with vector data description	Simulated data and industrial data from a steelmaking process	Multichannel profiles of the BOF steelmaking process	The proposed method outperforms all the compared models in terms of the anomaly detection rate. The method is time-efficient for online monitoring for industrial processes with a sampling frequency of no more than 96 Hz.
Cardoso et al. [67]	Predicting silicon content in hot metal production in blast furnaces	ANN model with sigmoid activation function and the Levenberg–Marquardt algorithm	A database of 82,500 data points from 1100 operational days	A total of 75 input variables classified into different groups (blow air, temperature, top gas, others) and one output: silicon content	A neural network model with 30 hidden neurons outperformed other models in predicting silicon content in hot metal production, indicating that big data and database treatment can enhance modelling accuracy.
Wang et al. [68]	Predicting the silicon content in hot metal in a blast furnace	MPC based on a multiobjective evolutionary algorithm (MOEA) and evolutionary feature selection (EFS)	Benchmark and actual industrial datasets	Twenty input features including former silicon content, hot air pressure, oxygen enrichment rate, hot air temperature, set amount of pulverised coal injection, blast kinetic energy, gas permeability, and dry dust removal inlet temperature	The MOENE-EFS method outperforms other ensemble soft computing methods for silicon content prediction. The proposed ELM_ENSEMBLE method is significantly superior to the two commonly used linear ensemble methods. The MOENE-EFS method achieves better performance than the MOEE-ELM, EL. NSDE1-ANN, and CNE-ELM methods.

Table 6. *Cont.*

Paper	Problematic	Method	Data Used	Specific Variables	Results
Yang et al. [69]	Filling missing data in a blast furnace gas system of the steel industry	Deep convolutional network (D-CNN)	Operation data from an iron and steel operation industry	Data related to the industrial blast furnace gas system operation data, specifically missing data from the hot blast stove in the gas system	The proposed method has higher data filling accuracy than existing methods and conforms to the actual distribution of samples. The network can accurately fill in the high proportion of random missing data.
Zhao et al. [70]	Develop an optimised control model for the matte grade in the copper smelting process	ANN and GA-BP neural network prediction model	A dataset with 910 samples obtained from industrial operation	Input variables: S, Fe, SiO_2, and CaO content in copper concentrate, oxygen volume, blast volume, and flux amount. Output variable: Term of matte grade	The ANN model was more accurate, with a matte-grade absolute error simulation of 0.51%, which is 56.41% lower than the matte-grade BP neural network prediction model.

The method applied depends on the specific problem and the characteristics of the data available. Dynamic modelling and simulation can be valuable approaches in situations where a comprehensive understanding of the fundamental physical processes is required, and there are established mathematical models that can serve as a foundation for simulation. The use of ANN is typically associated with vast amounts of available data and intricate correlations between input and output variables that traditional statistical models cannot simply represent. When dealing with large datasets with many variables, feature selection methods can help identify the most relevant variables for modelling purposes, reduce computational complexity, and improve model accuracy. Using a hybrid model may be an option when there are complex relationships between input and output variables that cannot be easily captured by a single model.

In the case of ANN application, different studies were analysed, where Gui et al. [60] generated a model with better estimations and higher precision compared to traditional regression models, where the root mean square error (RMSE) was reduced by 19.23% and the training decreased from 22.8 to 12.4 s. Using the integrated model, the RMSE is further decreased by 23.80%. These experiments were organised using an orthogonal design of the four-factor regression of the second degree, and the corresponding gold content in each experiment was measured. Ghea Puspita et al. [64] used an ANN method to optimise the reduction process of saprolite ore composites, and an optimal factor combination was found. The results were validated through the chemical compositions (mass%) of Fe, Al, and Si. Savic et al. [63] used statistical modelling approaches such as multiple linear regression analysis, artificial neural networks, and an adaptive network-based fuzzy inference system (ANFIS), where this approach was found to be the most accurate in predicting copper losses in the silicate slag of the sulphur concentrate smelting process, with a coefficient of determination of 0.989 in the training stage and 0.719 in the testing stage. J. Liu et al. [62], Cardoso et al. [67], and D. Liu et al. [28] developed an artificial neural network model to predict the production and quality control of hot metal in a blast furnace. The results show that the neural model is a useful tool to support the operation of an iron blast furnace, where more than 90% of predictive values fall into the range of 0.5% to 2%, which is consistent with the practical production process. Through this, high levels of mathematical correlation demonstrate the effectiveness of the model in predicting sulphur and phosphorus. Regarding the application of dynamic modelling and simulations for predicting matte grades, Zhao et al. [70] found a BP neural network prediction model that, using a sample amount of 910 data points (900 for training and 10 for testing), is effective in providing guidance for controlling the copper flash smelting process with a maximum relative error of 3.3% and an average relative error of 0.54%. Yang et al. [69] focus on the same process, developing and validate a dynamic model where the outcomes demonstrate that the hybrid intelligent model proposed in these publications is effective in predicting matte grade with high accuracy and reliability.

Wang et al. [68] proposed a nonlinear ensemble model based on a multi-objective evolutionary algorithm (MOEA) and evolutionary feature selection (EFS) to predict the silicon content in hot metal, which is an important indicator for judging the operating status of a blast furnace and achieved significantly better and more stable prediction performance.

Haar wavelet decomposition, PCA, and Mahalanobis distance with functional support vector data description (SVDD) are used by Qian et al. [66] to predict the silicon content of hot metal. The results show that the proposed method outperforms other methods in the literature for silicon content prediction. Wang et al. [68] and Deng et al. [61] featured the selection of methods for data-driven modelling of complex pyrometallurgical processes. These studies show that these methods can effectively select relevant features from large datasets, improving the accuracy and efficiency of data-driven models.

From the studies applied to mineral pyrometallurgical processes, the most relevant variables that have been identified include:

(a) Blowing air variables: This includes parameters such as the blowing flow rate, airspeed, and oxygen enrichment.
(b) Top gas variables: These variables are related to nitrogen and oxygen flow rates.
(c) Temperature variables: These are related to parameters such as flame temperature and hot metal temperature.
(d) Fuel variables: These include parameters such as coke and pulverised coal consumption rates.
(e) Ore variables: These variables are related to parameters such as pellet, sinter, and iron ore consumption rates.
(f) Hot metal variables: These variables are related to the content of hot metal in production and may include carbon, silicon, manganese, and phosphorus.
(g) Slag variables: These variables are related to the production of slag and include slag basicity and volume.

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

Figure 5 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 (R2); and computational efficiency scores are based on the characteristics and advantages of the methods in the papers.

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.

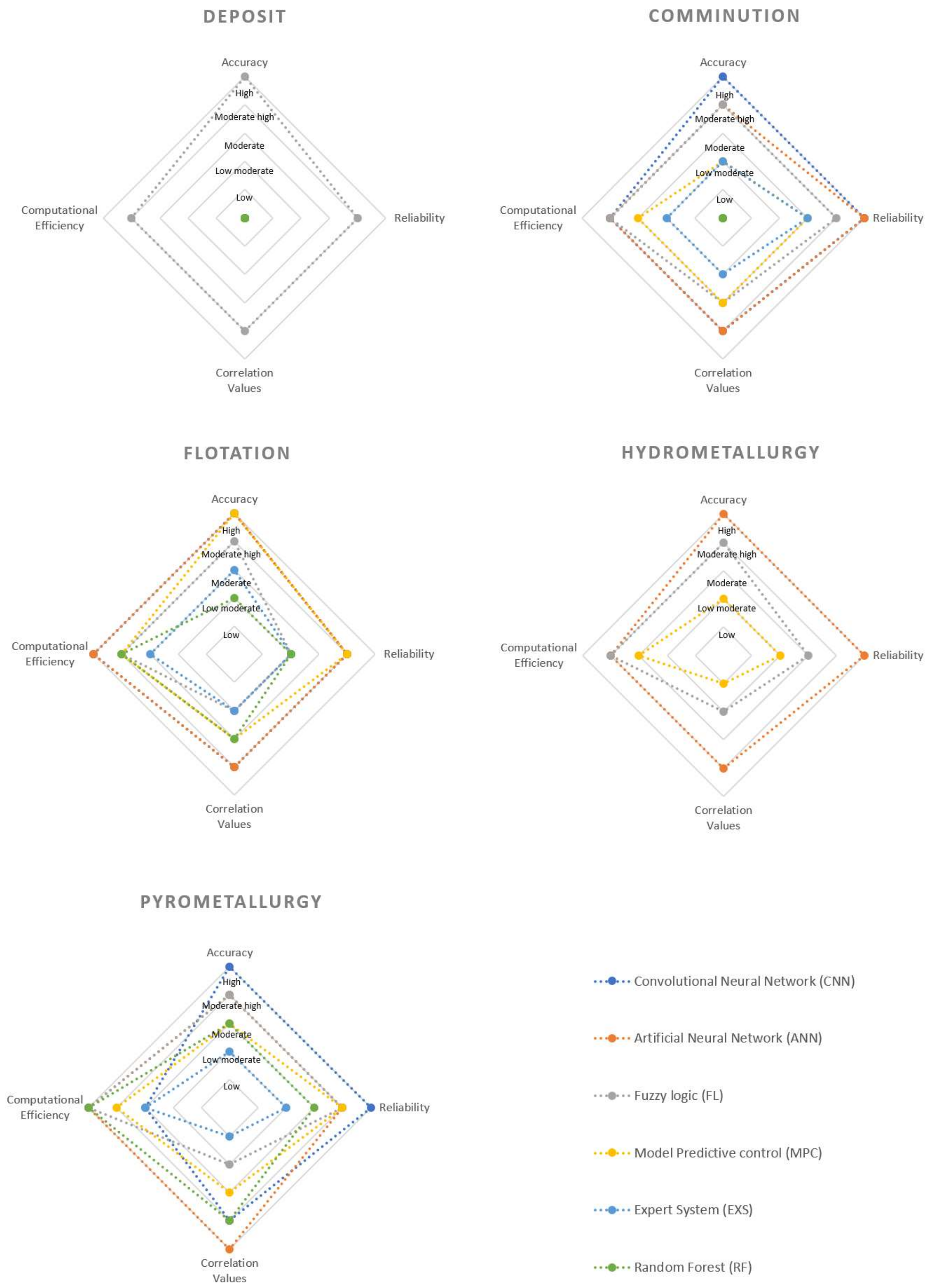

Figure 5. Qualitative comparison of soft computing methods applied in mineral processing.

4. 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 [74,91]. 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 [74], while the use of continental water consumption exceeds 0.36 m^3/ton of ore, with the consumption expected to rise further [92]. 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 [93], Finland [94], and Canada [95], 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 [96,97]:

- 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. In this approach, we establish the relevance of pulp characterization as a part of a predictive model of fluency behaviour for tailings and leaching waste ore generated from variables that are currently measured at mining sites.

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 [98]. 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 [99]. 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 [100]. This scope can solve the "catastrophic forgetting"; however, this method needs important periods of time in order to update the data continuously [61]. 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 [101].

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 6 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 7 presents an analysis framework that explores potential connections using various soft computing techniques, including neural networks. This framework incorporates training, prediction, and confirmation stages.

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.

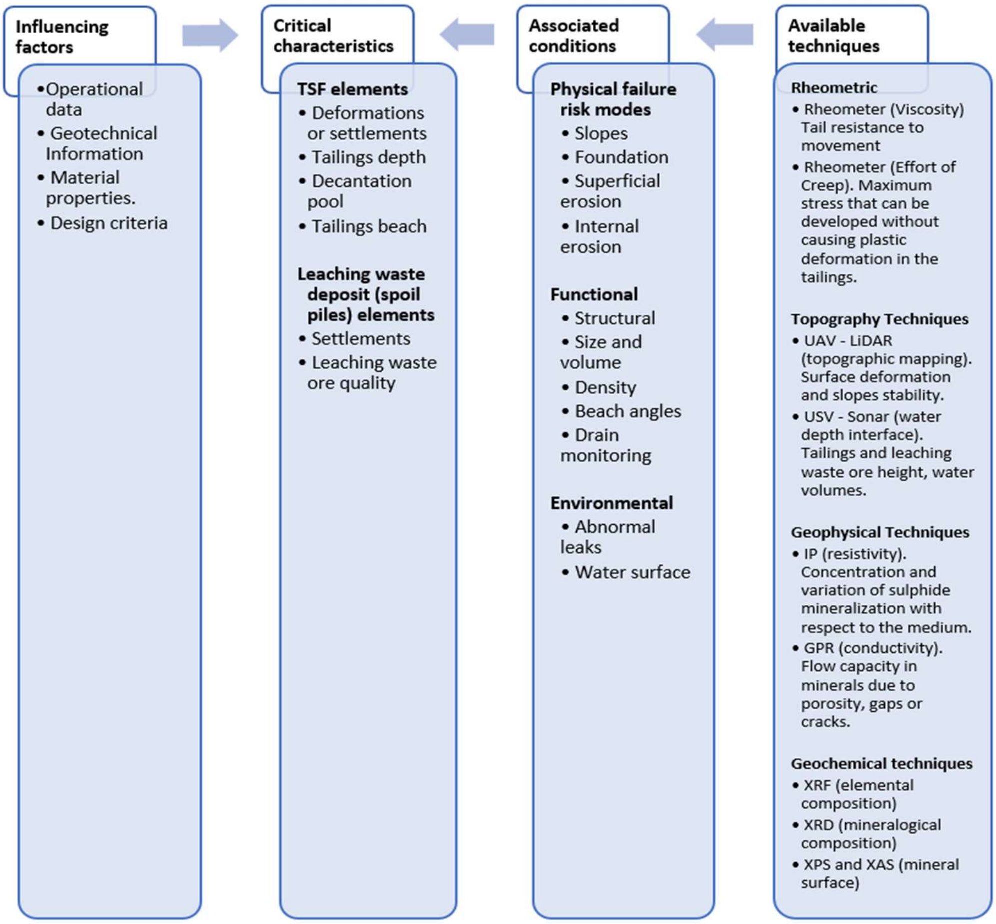

Figure 6. Parameters for a database generation for TSF and LWD.

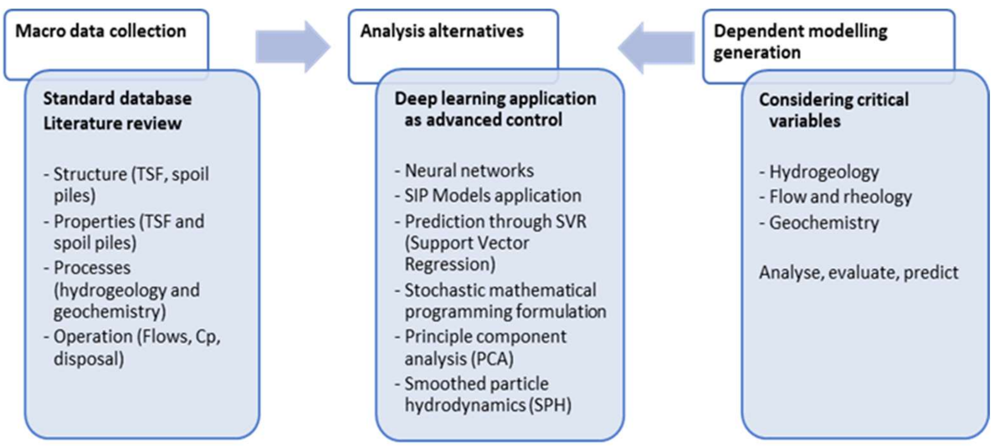

Figure 7. Example of possible correlations between parameters with different soft computing techniques.

5. Conclusions

This research provides compelling evidence for the growing adoption of soft computing as a viable solution in the design, development, and operation of intelligent systems for various phases of mineral processing and metal extraction operations. Soft computing has the ability to adapt, learn, and act independently in the mining industry. By considering the problem at hand, the characteristics of the environment, and the variables involved, it can develop and compute solutions to complex problems. Given the complex and non-linear nature of the processes involved, selecting the appropriate type of soft computing method becomes crucial when considering the various options available, such as artificial neural networks, expert systems, fuzzy algorithms, and more. These alternatives present interesting opportunities for addressing the complex and multivariable behaviours displayed by the processes, opening up new avenues for analysis and optimisation.

This publication presents the considerable potential of sophisticated technologies and tactics in enhancing safety, decision-making processes, and plant performance within the mining and mineral processing sectors. Fuzzy logic, machine vision, artificial neural networks, and advanced measurement technologies are among the key tools discussed. The effectiveness of these approaches is demonstrated in areas such as risk assessment, accident prediction, process modelling, control performance improvement, prediction accuracy enhancement, optimal condition determination, and composition estimation. Additionally, the importance of feature selection, soft computing approach selection, big data utilisation, and database treatment is emphasised. Further research is suggested in areas such as froth image analysis, where, thanks to the fact that image acquisition technologies have been evolving and reducing costs, it is possible to apply soft computing and reliable data linking to help optimise mineral recovery performance and improve profitability, reduce operational costs, and enhance real-time monitoring of froth properties. Overall, the integration of advanced technologies, control strategies, and data-driven approaches holds great promise for optimising processes, enhancing efficiency, and reducing instability in the mining industry. On the other hand, as our investigation shows, there is a real possibility of implementing soft computing in other critical processes for operational continuity in the mining industry, such as the transport and deposit of tailings and spent heap leaching. We have successfully identified key variables that are crucial for the successful implementation of soft computing techniques in various industrial applications. These variables can be effectively monitored and collected at an industrial level. For comminution stages, important variables include the feed rate, screen aperture size, and crusher rotor speed. In deposit studies, variables such as the deposit element grade, tonnage, mining and processing costs, and metal prices play a significant role. In pyrometallurgical processes, variables such as the temperature, gas flow rate, and particle size distribution of the feed material are essential. Additionally, in processes involving froth and leaching, variables such as the bubble size, froth class, viscosity, pH, temperature, leaching time, and concentrations of sulfuric acid and copper in the leach solution are critical factors to consider.

The creation of a comprehensive database derived from diverse mining operations can facilitate the identification of shared characteristics and develop correlations among essential mineralogical parameters. Incremental learning through artificial neural networks can aid in operational decision-making. Analysing variables such as hydrogeology, flow, rheology, and geochemistry can be a good approach to the implementation of this type of technology for the control of mining waste. Finally, the application of this type of technology over time does not depend on the application of the tool itself but on the source, availability, and quality of the data that can be obtained.

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