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Optimization of Grinding Mill Parameters using Genetic Algorithms for Energy Efficiency in Mining Industry

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Abstract

Energy efficiency and product quality control are critical concerns in grinding mill operations, particularly within the innovative context of Mine 4.0. This study introduces a novel Genetic Algorithm (GA)-based optimization framework specifically developed to address these challenges. Given the mining industry's significant energy consumption, especially in grinding processes, the proposed approach optimizes key parameters such as feed composition, water flow rates, and power consumption levels, while maintaining sieve refusal near the target threshold of 20%. Using real operational data from a Moroccan plant, the GA achieved a Mean Absolute Error (MAE) of 0.47, outperforming Simulated Annealing (SA) and Particle Swarm Optimization (PSO), which yielded MAEs of 1.14 and 0.74, respectively. The GA also demonstrated superior convergence stability and robustness, as evidenced by lower variability in predicted power consumption. These results validate the effectiveness of the GA framework in navigating nonlinear, high-dimensional parameter spaces and improving energy efficiency while ensuring product quality consistency. Ultimately, this research confirms the potential of metaheuristic optimization in enhancing grinding mill efficiency and supports the broader shift towards intelligent and sustainable mining operations under the Mine 4.0 paradigm.

1. Introduction

The advent of Mine 4.0 marks a transformative shift in the mining industry, characterized by the integration of cutting-edge analytics and artificial intelligence (AI) into conventional resource extraction processes [1]. This paradigm shift has accelerated improvements in operational performance, productivity, efficiency and overall safety. AI-based solutions [2], [3], [4], [5] are increasingly employed to optimize various stages of mining, contributing to notable reductions in production costs and energy consumption [6]. These trends underscore the impact of Mine 4.0 [7], [8], which leverages large-scale data collection, cloud-based processing, and real-time monitoring to revolutionize process management and decision-making in complex industrial environments [9], [10], [11].

Within this domain, energy consumption stands out as a primary concern. Globally, the mining sector accounts for about 11% of total energy use, 38% of industrial energy consumption, and 15% of worldwide electricity usage [12]. Grinding mills in particular are notoriously energy-intensive [13], as they reduce ores through repetitive impact and abrasion. These processes not only demand substantial power but also play a pivotal role in determining the overall throughput and product quality of mining operations.

Efforts to optimize grinding mills typically focus on regulating both power usage and material

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properties—one of the most important being the sieve refusal, which reflects the proportion of oversized particles remaining after grinding. In many applications, maintaining a specific sieve refusal target (often around 20%) is vital to uphold product specifications and ensure efficient downstream processing [14]. Striking the right balance between product quality and minimizing energy usage is a challenge that often requires advanced algorithms capable of handling non-linear, high-dimensional search spaces [15].

Motivated by these demands, researchers have begun incorporating metaheuristic optimization algorithms to enhance the performance of grinding operations under diverse and dynamic conditions. Metaheuristics—such as (GA) [16] [17], Simulated Annealing (SA) [18], and Particle Swarm Optimization (PSO) [19] are powerful tools for managing multi-objective, constraint-rich problems. These algorithms can handle varied input parameters including feed water, feed tonnage, and system power levels. By iteratively searching for improved parameter sets, metaheuristics can converge toward operational settings that lower energy consumption while maintaining sieve refusal near its target threshold [20].

While recent research has demonstrated the potential of AI and metaheuristic algorithms in optimizing mining processes, several critical gaps persist in the current literature [21]. Firstly, many existing studies adopt narrow optimization scopes, focusing on individual parameters without accounting for the inherent trade-offs between energy consumption and product quality [22]. Secondly, although metaheuristics such as GA, SA, and PSO have been explored, comparative studies that rigorously evaluate their effectiveness in controlling sieve refusal—an essential quality indicator in grinding operations—remain limited[23]. Furthermore, most approaches lack integration with real operational constraints and fail to generalize across variable process conditions [24] [25]. In response to these limitations, this study proposes a novel optimization framework based on Genetic Algorithms, specifically designed to balance energy efficiency with product quality in grinding mills. By incorporating real-world industrial data and conducting comparative analyses against SA and PSO, the proposed approach not only bridges an important gap in the literature but also demonstrates superior robustness and adaptability. The originality of this work lies in its dual-objective formulation and its capacity to handle the complexity of multi-parameter optimization in energy-intensive mining environments, thereby underlining its necessity and relevance to advancing Mine 4.0 strategies.

This study presents a novel Genetic Algorithm–based optimization approach tailored to grinding mills, designed to meet both energy-efficiency and product-quality requirements simultaneously. Specifically, the GA explores sets of input parameters—encompassing feed composition percentages, feed water flow rates, and targeted power levels—to maintain sieve refusal at around 20%, ensuring consistency in particle size distribution. Preliminary comparisons with other metaheuristics, such as SA and PSO, demonstrate that the GA framework can yield more stable solutions and closer adherence to the desired refusal range. In summary, the primary contributions of this paper include:

- (1) A GA-based optimization framework that balances energy usage with product quality constraints in grinding mills.
- (2) Integration of real operational data and domain-specific factors, including feed composition, feed water, and power draw, to guide the search process.
- (3) A comparative analysis of alternative metaheuristics (SA and PSO), highlighting the robustness and effectiveness of the proposed GA solution.

The remainder of this paper is organized into distinct sections. Section 2 reviews relevant grinding mill technologies and parameters affecting energy consumption and sieve refusal. Section 3 details the proposed GA-based approach, including the formulation of its objective function and operational constraints. Section 4 evaluates performance on industrial datasets and compares the GA with SA and PSO under identical scenarios. Finally, Section 5 discusses the major findings, potential implications, and avenues for future work.

2. Materials and Methodology

2.1. Rod grinding mills

The rod grinding mills at the CMG plant, a Moroccan mining facility, process lead, copper, and zinc ores mixed with water after primary crushing. These mills are responsible for reducing the particle size of the ore from an initial D80 of 10 mm to a finer D80 of 500 µm. This reduction is achieved through continuous feeding and rolling actions, where rods grind the ore via impact and abrasion within a watery suspension. The grinding process utilises an overflow system, and a hydrocyclone is employed to classify particles, separating them into overflow and underflow based on their D80 sizes [26].

Rod grinding mills are energy-intensive equipment in the mining industry. Two phenomena in the grinding process over-grinding and under-grinding lead to energy losses. Overgrinding causes electrical energy loss in the grinder and reactive energy loss in the flotation cells, while under-grinding results in electrical energy loss during regrinding as well as ore loss in flotation. Therefore, rod grinding mills consume more energy during their operation. Optimizing this energy consumption in real time can help identify these energy losses and optimise the process for energy efficiency in rod grinding mills [27].

2.2 Dataset

Based on both on-site evaluations at the CMG plant and comprehensive research, several key parameters have been identified as the main determinants of grinding mill energy consumption. These include the mill's feed tonnage, feed water usage, electrical power draw, the proportion of minerals sourced from different mines, and the sieve refusal of the mill's discharge. All variables were obtained from operational data collected by sensors installed in the rod grinding mills, with measurements recorded every minute for feed tonnage (t/h), feed water (m^3/h), and power (kW). The ore processed in these mills originates from three distinct mine sources, each contributing a variable proportion based on the CMG plant's operational requirements. Additionally, the sieve refusal—the percentage of particles larger than 500 µm—fluctuates around 20%, a level deemed optimal for enhancing the energy efficiency of the grinding mills.

Building on these insights, the present research develops an optimization model grounded in a dataset that consolidates the composition of three ore types—Ore 1, Ore 2, and Ore 3—alongside the key operational parameters of feed tonnage, feed water, and power consumption. Each record in the dataset thus captures the proportion of each ore type together with corresponding parameter values, enabling a systematic analysis aimed at minimizing any deviation of sieve refusal from the 20% target. By integrating ore composition data with these critical performance indicators, the model provides a robust foundation for identifying energy-efficient configurations and improving overall grinding efficiency.

2.3. Processing dataset

Constructing a dataset that accurately reflects the operational characteristics of grinding mills begins with standardizing the frequency of all variables to one observation per minute. Following this, all variables are consolidated into a single dataset. During the integration process, rows containing NaN values or columns with one or more zero values are removed to ensure data quality. Consequently, the finalized dataset comprises 256,659 observations. Table 1 provides a summary of the key statistical properties of the dataset. All values were calculated using Python's Pandas library after data cleaning, and reflect real operational conditions captured through one-minute interval logging.

Table 1. Statistical summary of grinding mill variables.

Variables	Min	Max	Mean	Stdv
Feed Water (m3/h)	1.28	62.63	10.53	1.49
Feed Tonnage (T/h)	1.88	181.91	118.32	13.33
Power (KW)	8.22	718.69	508.57	42.00
Sieve Refusal (%)	12.69	54.21	24.91	5.45
Ore 1 (%)	0	100	81.65	17.56
Ore 2 (%)	0	100	14.92	8.93
Ore 3 (%)	0	100	3.43	18.20

2.4. Correlation matrix

The correlation matrix, illustrated in Figure 1, was generated using the pearson correlation coefficient, which quantifies linear relationships between variables in the cleaned dataset. It is employed to examine the degree of association among the dataset variables. The correlation coefficient, ranging from -1 to 1, indicates both the strength and direction of these relationships. A positive coefficient (greater than 0) suggests that as one variable increases, the other also increases, with higher values denoting stronger positive relationships. Conversely, a negative coefficient (less than 0) implies that as one variable increases, the other decreases. A value of 0 indicates no linear relationship between the variables [28].

To optimize grinder performance and improve energy efficiency, it is crucial to consider feed tonnage, feed water, and power consumption together. Feed tonnage balances the risk of under-grinding and over-grinding, affecting overall throughput. Feed water regulates pulp density, which influences grinding kinetics and particle size reduction, making its adjustment important for efficient energy use. Meanwhile, power consumption, driven by ore properties and feed conditions, is a major cost factor; identifying the optimal power input is therefore vital to minimizing excess energy expenditure. The correlation matrix illustrates how these factors interact, providing a valuable tool for integrated optimization. By incorporating the specific percentages of each ore type in the feed, this study determines the best combination of feed tonnage, feed water, and power to achieve the desired sieve refusal and enhance both grinding efficiency and energy conservation.

Notably, the correlation between time and power is negative (-0.41). This trend reflects daily operational patterns at the CMG plant, where energy consumption is typically higher during peak production hours (daytime shifts) and significantly lower during off-hours or maintenance periods, such as overnight shifts or early mornings. Since "Time" is treated as a continuous variable representing the sequence of records (not cyclic hours), this negative correlation captures the operational cycle of reduced activity as time progresses within each day.

In addition to the negative correlation between time and power, the matrix reveals that feed tonnage and ore composition variables exhibit relatively weak correlations with power consumption (e.g., feed tonnage: -0.13; Ore 2: -0.35). This highlights the non-linear and multidimensional nature of the grinding process, which justifies the use of metaheuristic optimization techniques such as GA to capture complex interactions beyond simple linear trends.

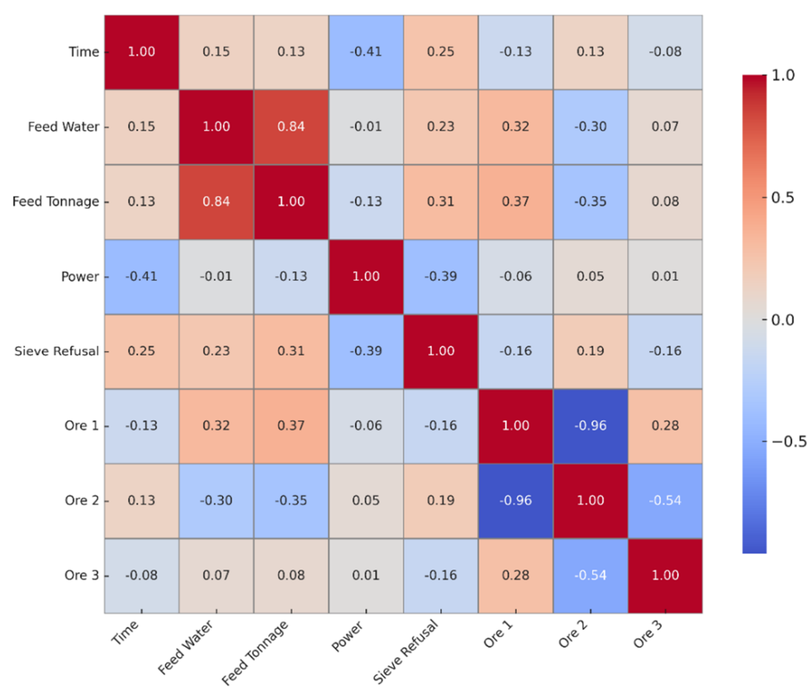


Figure 1. Correlation matrix highlighting linear dependencies among process parameters.

2.5. Performance metric

In this study, the model's predictive accuracy is assessed exclusively using the Mean Square Error (MSE). The MSE measures the average squared difference between predicted sieve refusal values and ideal values, thus penalizing larger errors more heavily [29]. Equation (1) illustrates the computation, where a lower MSE indicates a better predictive performance:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} | \hat{y}_i - y_i | \quad (1)$$

Where $\hat{y}_i$ is the predicted value, y_i is the actual value, and n is the total number of observations.

In addition to MSE, further evaluation metrics were introduced to provide a more comprehensive assessment of model accuracy. The Mean Absolute Percentage Error (MAPE) [30], defined in

Equation (2), expresses the average prediction error as a percentage of the actual value, offering a scale-independent measure particularly useful for comparative analysis:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (2)$$

To evaluate the relative magnitude of prediction error with respect to the variability of the target variable, we also compute the standard deviation of the target σ_{target}, as presented in Equation (3). This metric characterizes the natural dispersion of actual sieve refusal values:

$$\sigma_{target} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

$$where\ \bar{y} = \frac{1}{n}\sum_{i=n}^{n} y_i$$

Finally, we use the standardized mean absolute error (sMAE) to normalize the MAE by the standard deviation of the target, offering a unitless measure of relative error that facilitates model comparison. The sMAE is defined in Equation (4):

$$\text{sMAE} = \frac{\text{MAE}}{\sigma_{target}} \quad (4)$$

A lower sMAE value indicates that the model's absolute error is small relative to the natural variability of the target variable, confirming the robustness and high precision of the proposed predictive model.

3. Proposed Method

This paper proposes a Genetic Algorithm (GA) model dedicated to optimizing grinding mill parameters, thereby enhancing efficiency and product quality. The GA operates by encoding each potential solution (e.g., combinations of feed water, feed tonnage, and power settings) as a chromosome, which is then iteratively refined through biologically inspired operators such as selection, crossover, and mutation. This population-based methodology ensures that high-fitness solutions are systematically exploited while maintaining enough genetic diversity to avoid premature convergence. Unlike traditional optimization methods, the GA effectively navigates the large, multidimensional space of grinding parameters, which is characterized by substantial time delays and nonlinear interactions. Figure 2 depicts the conceptual flow of this GA model, illustrating how candidate solutions evolve from one generation to the next in pursuit of near-optimal performance [31], [32], [33], [34], [35], [36].

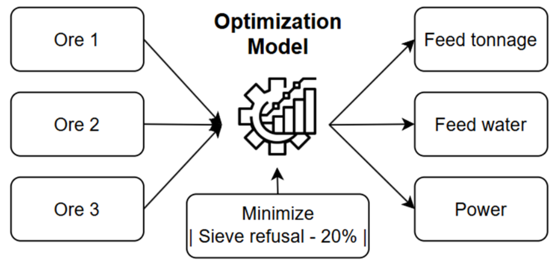


Figure 2. Optimization model linking ore inputs to process controls.

3.1. Genetic algorithm architecture

To optimize the grinding mill operation, a genetic algorithm is used to determine the best combination of feed parameters based on the ore blend. The inputs to the algorithm are the percentages of Ore 1, Ore 2, and Ore 3. Based on these, the algorithm adjusts feed water, feed tonnage, and power to achieve optimal performance. The following steps describe the full GA process, from initialization to final solution.

3.1.1. Initialization

The genetic algorithm begins by generating an initial population of n chromosomes, denoted by $\left\{Y_1^{(0)}, Y_2^{(0)}, \dots, Y_n^{(0)}\right\}$. Each chromosome $Y_i^{(0)}$ is typically a vector or other representation of a candidate solution to the optimization problem. The manner in which these chromosomes are constructed (e.g., random initialization, heuristic methods) strongly influences how rapidly the search space is explored.

3.1.2. Fitness evaluation

After initialization, we assign an iteration counter t = 0. We then evaluate each chromosome in the population by computing its fitness using a predefined function $f\,(Y_i^{(t)})$. This fitness function quantifies how well a given chromosome satisfies the objectives and constraints of the problem, with higher fitness values indicating better solutions. Mathematically, the population's total or average fitness can be expressed as shown in Equation (5):

$$F_{pop}^{(t)} = \sum_{i=1}^{n} f\ (Y_i^{(t)})\ \ or\ \ \bar{F}_{pop}^{(t)} = \frac{1}{n}\sum_{i=1}^{n} f\ (Y_i^{(t)}) \quad (5)$$

3.1.3. Selection

During each iteration t, as long as t < MAX, the algorithm selects pairs of chromosomes from the current population based on their fitness values. A common mechanism is proportionate selection, in which a chromosome $Y_i^{(t)}$ is chosen with the probability defined in Equation (6):

$$P(Y_i^{(t)}) = \frac{f\ (Y_i^{(t)})}{\sum_{k=1}^{n} f\ (k_i^{(t)})} \quad (6)$$

Other selection methods such as tournament selection, rank-based selection, or roulette wheel selection can also be employed. The idea is to bias the selection toward chromosomes with higher fitness, while still allowing less-fit chromosomes a chance to be chosen, thus maintaining genetic diversity.

3.1.4. Crossover

Once two parent chromosomes $Y_p^{(t)}$ and $Y_q^{(t)}$ are selected, they undergo a crossover operation with probability p_c. A common approach is single-point crossover, where one crossover point is chosen at random along the chromosome representation, and portions are swapped to produce offspring $\tilde{Y}_r^{(t)}$ and $\tilde{Y}_s^{(t)}$. In a single-point crossover, for instance, if the crossover point is c, the offspring are generated as shown in Equation (7):

$$\tilde{Y}_r^{(t)} = \left(Y_p^{(t)}[1{:}c],\ \ Y_q^{(t)}[c+1{:}L]\right), \qquad \tilde{Y}_s^{(t)} = \left(Y_q^{(t)}[1{:}c],\ \ Y_p^{(t)}[c+1{:}L]\right) \quad (7)$$

where L denotes the length of the chromosome representation. More advanced crossover techniques, such as multi-point or uniform crossover, can also be utilized.

3.1.5. Mutation

After crossover, each offspring is subjected to a mutation operator with probability pm. Mutation introduces random alterations to the offspring's genes, which helps prevent premature convergence by diversifying the population. A simple example is bit-flip mutation for binary chromosomes Equation (8):

$$Y\begin{cases} 1-\tilde{Y}_r^{(t)}, & with\ probabiity\ p_m \\ \tilde{Y}_r^{(t)}[j]\ , & otherwise \end{cases} \quad (8)$$

For real-valued chromosomes, mutation might involve adding a small random value drawn from a specified distribution (e.g., Gaussian).

3.1.7. Termination and best solution

The above sequence of steps repeats until the iteration counter reaches the maximum allowable number of iterations, MAX, or until a specified convergence criterion (e.g., lack of improvement in fitness) is met. Upon termination, the algorithm returns the best chromosome, as defined in Equation (9):

$$Y_{bt} = \arg \max_{Y\in final\ population} \{f(Y)\}\ , \quad (9)$$

which represents the GA's best-known solution to the given optimization problem. By balancing selection pressure, crossover-driven exploration, and mutation-induced diversity, the Genetic Algorithm seeks to converge on high-fitness solutions over successive generations.

Overall, this Genetic Algorithm framework effectively handles the complexity and delays inherent in grinding mill operations by iteratively refining parameter combinations. Through selection, crossover, and mutation, the GA converges on near-optimal solutions that balance efficiency and product quality without becoming trapped in local optima, making it a robust tool for industrial process optimization.

3.2. Optimization and hyperparameters for genetic algorithm

To conduct the optimization experiments, the Genetic Algorithm was configured with the hyperparameters summarized in Table 2. Specifically, the population size was fixed at 50, thereby ensuring sufficient diveOrsity among candidate solutions without excessively increasing computational cost. In each run, the algorithm iterated for 100 generations, allowing the population to evolve through successive cycles of selection, crossover, and mutation. The crossover rate was set to 0.8, encouraging substantial recombination of promising genetic material and facilitating the creation of offspring that inherit advantageous traits from their parents. Meanwhile, the mutation rate of 0.1 introduced a controlled level of stochastic variation, mitigating the risk of premature convergence by exploring new regions of the parameter space. Collectively, these hyperparameter choices balanced the twin objectives of thorough exploration and efficient convergence toward high-quality solutions.

All simulations were performed on a Lenovo Legion system (Model 82JQ) equipped with an AMD Ryzen 7 5800H processor (16 logical cores, ~3.2 GHz), 32 GB of RAM, and a dedicated NVIDIA GeForce RTX 3070 Laptop GPU with 8,033 MB of dedicated video memory and approximately 22,295 MB total graphics memory. The experiments were conducted under Windows 11 (64-bit, build 26100) with DirectX 12, using Python and scientific libraries including NumPy and SciPy. This configuration ensured sufficient computational resources for handling the algorithm's iterative processes and evaluating large-scale parameter combinations efficiently.

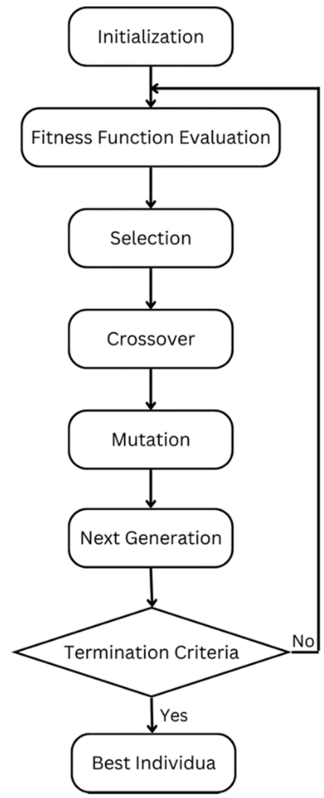


Figure 3. Workflow of the Genetic Algorithm during parameter optimization.

Table 2. Genetic algorithm parameters for grinding optimization.

Hyperparameter	Value	Description
Population size	50	Number of individuals in the population per generation.
Num generations	100	Number of generations (iterations) the GA will run.
Crossover rate	0.8	Probability of applying crossover (mating) to each selected pair.
Mutation rate	0.1	Probability that any given gene (parameter) is mutated.

4. Results and Discussion

In order to underscore the effectiveness of our Genetic Algorithm (GA) in optimizing energy consumption, we conducted a comparative study against two well-known metaheuristic techniques, namely Simulated Annealing (SA) and Particle Swarm Optimization (PSO). By running each algorithm under identical conditions and datasets, we systematically evaluated their performance using metrics such as mean absolute error (MAE). This rigorous analysis enabled a fair comparison of solution accuracy, convergence speed, and overall robustness across the three distinct approaches.

4.1. Optimization grinding mill variables

The Genetic Algorithm (GA) proposed in this work demonstrates significant potential in optimizing the operational parameters of grinding mills, particularly in achieving accurate predictions of the desired output, such as maintaining sieve refusal close to 20%. To thoroughly evaluate the performance of the GA, we conducted a comparative analysis with two widely used metaheuristic optimization techniques: Simulated Annealing (SA) and Particle Swarm Optimization (PSO). This comparison aims to highlight the strengths and limitations of each algorithm when applied to the complex, multi-variable environment of grinding mill optimization. Figures 1 through 3 present the results of these algorithms, where the ideal target value is represented by the blue line, and the predicted values generated by each algorithm are depicted as red dots.

The GA's performance, as illustrated in Figure 4, shows a tight clustering of predicted values around the ideal target. This indicates the algorithm's strong ability to minimize deviations, reflecting both precision and consistency across different iterations. The evolutionary mechanisms embedded in the GA—selection, crossover, and mutation—allow for continuous refinement of candidate solutions, ensuring that high-quality solutions are retained and improved over successive generations. This iterative improvement process facilitates the GA's ability to explore a wide search space effectively while avoiding premature convergence to suboptimal solutions.

In contrast, the performance of PSO, depicted in Figure 2, reveals a more scattered distribution of predicted values. While PSO demonstrates the capability to approximate the ideal target, several predictions deviate significantly, particularly in regions where the system's dynamics are more complex. PSO's reliance on the social behaviour of particles to converge towards optimal solutions can sometimes lead to stagnation around local optima, especially in problems characterized by high-dimensional search spaces with complex constraints. Despite this, PSO still manages to capture the general trend of the target output, showcasing its robustness and efficiency in certain scenarios.

Simulated annealing, as shown in Figure 4, exhibits the most variability among the three algorithms. The predicted values are widely dispersed, with frequent and pronounced deviations from the ideal target. SA's stochastic nature, which relies on probabilistic acceptance of worse solutions to escape local optima, contributes to this variability. While this feature can be advantageous in avoiding local minima, it also leads to less consistent convergence, particularly in problems requiring fine-tuned precision. The lack of a population-based approach, as seen in GA and PSO, further limits SA's ability to maintain diversity and exploit multiple promising regions of the search space simultaneously.

Several factors contribute to the superior performance of the GA compared to SA and PSO. Firstly, the GA's population-based approach ensures that a diverse set of solutions is maintained throughout the optimization process, enhancing the algorithm's ability to explore and exploit the search space effectively. The crossover mechanism allows for the recombination of high-quality traits from different solutions, while mutation introduces necessary variability to explore new areas of the search space. This balance between exploration and exploitation is critical for achieving both global search capability and local refinement.

Moreover, the GA's adaptive selection process prioritizes high-fitness individuals, ensuring that the most promising solutions are preserved and further refined in subsequent generations. This contrasts with SA's reliance on a single solution pathway and PSO's tendency to converge prematurely in complex landscapes. The GA's ability to maintain multiple competing solutions simultaneously reduces the risk of convergence to suboptimal regions, a common challenge in high-dimensional optimization problems.

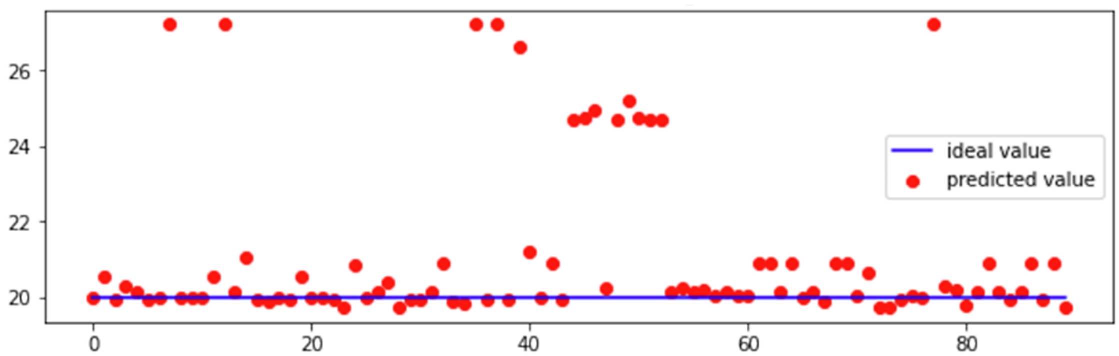
The comparative analysis clearly illustrates the advantages of the GA in optimizing complex industrial processes such as grinding mill operations. Its ability to balance exploration and exploitation, maintain solution diversity, and adaptively refine candidate solutions makes it a robust and reliable choice for achieving high predictive accuracy. While SA and PSO have their respective strengths and can be effective in specific contexts, the GA's superior performance in both convergence speed and predictive precision underscores its suitability for solving multi-variable, high-dimensional optimization problems. This study highlights the potential of GA as a powerful tool for process optimization in industrial applications, offering valuable insights for future research and practical implementations.

4.2. Model evaluation

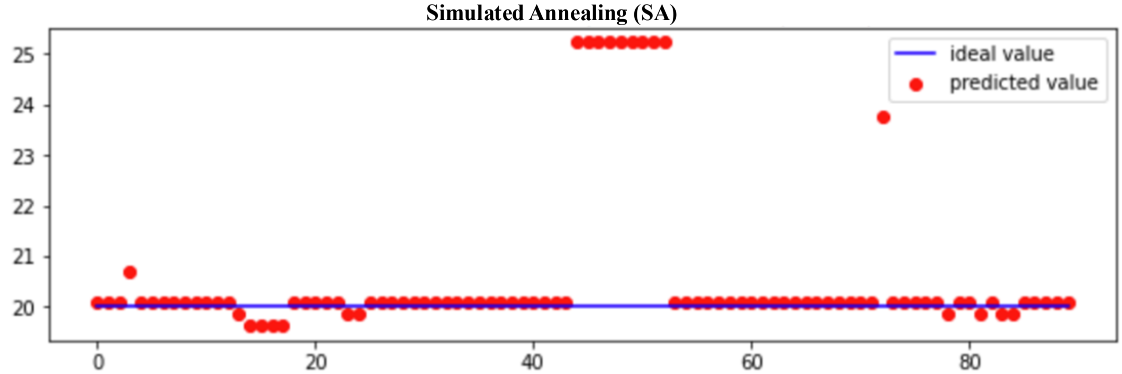
A comprehensive evaluation of three widely adopted metaheuristic optimization algorithms—Genetic Algorithm (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO)—is conducted, emphasizing their Mean Absolute Error (MAE) in predicting the target sieve refusal of 20%, as shown in Table 3. These algorithms were applied to optimize the proportions of DS, KA, and DSN, thereby influencing essential operational parameters such as feed tonnage, feed water, and power. Crucially, MAE serves as a robust and interpretable metric for quantifying the average deviation of model predictions from the observed values, making it a reliable benchmark for comparing optimization performance.

A closer look at the reported MAE values underscores the GA's effectiveness and robustness in converging on the near-optimal solution. Specifically, the GA exhibits the lowest MAE (0.47), indicating that, on average, its predicted sieve refusal is closest to the 20% target. This superior performance can be attributed to the GA's unique evolutionary mechanisms—namely crossover and mutation—that systematically introduce genetic diversity and facilitate extensive exploration of the solution space. Moreover, its population-based approach helps circumvent premature convergence, often encountered in less diverse search methods, ensuring a global rather than local optimum is more likely to be identified.

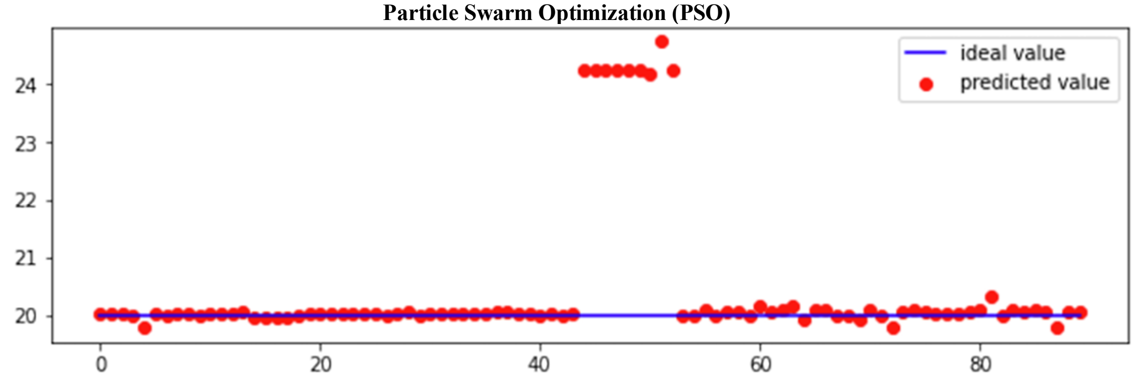
In comparison, the PSO algorithm, with an MAE of 0.74, demonstrates an intermediate capacity to converge on the desired target. While PSO's swarm intelligence and velocity-based position updates are typically advantageous for continuous optimization problems, its performance can be sensitive to parameter tuning (e.g., inertia weight, cognitive, and social coefficients). This sensitivity occasionally results in suboptimal exploration–exploitation trade-offs, thereby accounting for a higher mean prediction error than the GA. Its MAPE value of 3.7% and standardized MAE (sMAE) of 0.14 further reflect its moderate prediction accuracy and relative deviation from the target.



Simulated Annealing (SA)



Particle Swarm Optimization (PSO)



Genetic Algorithm (GA)

Figure 4. Algorithm performance in approximating the 20% sieve refusal target

Notably, the SA approach yields the highest error (MAE = 1.14), which signals that its stochastic iterative method—despite using a temperature-driven mechanism to escape local minima—may require careful tuning of annealing schedules, cooling rates, and initial solutions to reach competitive performance levels. In particular, SA may struggle when confronting high-dimensional or multi-variable domains if insufficient computational iterations are allotted, leading to slower convergence compared to PSO and GA. This is further supported by its MAPE of 5.7% and sMAE of 0.21, which indicate greater deviation from the ideal sieve refusal value and lower predictive reliability.

Overall, the GA stands out as the most accurate and consistent algorithm for this optimization task. Its relatively low MAE (0.47), MAPE (2.35%), and sMAE (0.09) highlight the algorithm's capacity to effectively navigate complex solution spaces, adapt to changing conditions, and refine the mixture formulation to precisely meet the 20% sieve refusal criterion. Consequently, these findings endorse the GA as the preferred choice among the three metaheuristics for research or industrial applications requiring rigorous and reliable optimization of multiple input variables.

Table 3. MAE results comparing GA, PSO, and SA performance.

Algorithm	MAE	MAPE	sMAE
Simulated Annealing (SA)	1.14	5,7%	0,21
Particl Swarm Optimization (PSO)	0.74	3,7%	0,14
Genetic Algorithm (GA)	0.47	2,35	0,09

4.3. Convergence robustness evaluation

The robustness of each metaheuristic algorithm was assessed by analyzing the rolling standard deviation of the predicted power throughout the optimization process. As illustrated in Figure 5, Particle Swarm Optimization (PSO) displayed the highest variability, with frequent oscillations and unstable convergence. Simulated Annealing (SA) exhibited moderate fluctuations before stabilizing, indicating that its performance can heavily depend on the cooling schedule and may involve exploratory detours into suboptimal regions. In contrast, the Genetic Algorithm (GA)—the proposed optimization method in this study—demonstrated superior stability, consistently maintaining low variability as it converged to high-quality solutions. This steady performance underscores GA's well-balanced approach to exploration and exploitation, enabling more dependable convergence patterns and limiting the risk of diverging toward unfavourable solution spaces.

Moreover, GA's convergence profile highlights its strong resilience to stochastic effects and minimal sensitivity to initial parameter settings, qualities that are particularly advantageous in industrial energy optimization. By effectively navigating complex search spaces and producing repeatable, high-quality results, GA offers a reliable mechanism for process adjustment and control. In practice, this robustness translates into tangible operational benefits, such as reduced downtime, more consistent power consumption, and the ability to accommodate fluctuations in ore properties and plant conditions without compromising system performance. Collectively, these findings reinforce GA as the preferred metaheuristic solution where robust, stable, and efficient optimization is paramount.

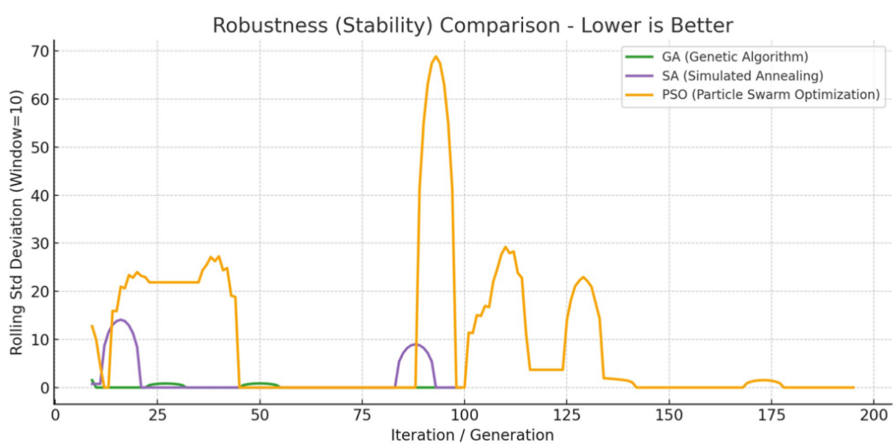


Figure 5. Convergence stability of GA, PSO, and SA based on power variability.

5. Conclusions

This research work presents a Genetic Algorithm (GA)-based optimization framework aimed at enhancing the operational efficiency of rod grinding mills by aligning energy consumption with product quality specifications, particularly maintaining sieve refusal near the target threshold of 20%. The model was trained and validated using real operational data from a Moroccan mining facility, ensuring the framework's practical applicability in industrial settings. The proposed GA demonstrated strong optimization performance, achieving a Mean Absolute Error (MAE) of 0.47, which significantly outperformed the MAEs obtained by Simulated Annealing (1.14) and Particle Swarm Optimization (0.74). In addition to accuracy, the GA exhibited superior convergence stability and robustness, with lower variability in power prediction and a more consistent alignment with optimal grinding conditions.

These results confirm the capability of the GA to navigate complex, nonlinear, and high-dimensional parameter spaces typically encountered in comminution circuits. By optimizing feed tonnage, water input, and power consumption, the framework successfully supports energy savings while ensuring product quality remains within specification. Although the GA shows robust performance, potential limitations include computational overhead when applied to larger-scale or real-time systems. Future work will focus on improving the computational efficiency of the model, possibly through hybridization with other techniques or by leveraging parallel processing, to enhance its scalability and integration into real-time Mine 4.0 systems. Overall, this study demonstrates that metaheuristic optimization, when applied to real-world data, can significantly contribute to intelligent, sustainable, and cost-effective mineral processing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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بهینه‌سازی پارامترهای آسیاب با استفاده از الگوریتم‌های ژنتیک برای بهره‌وری انرژی در صنعت معدن

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کلمات کلیدی

آسیاب‌های سنگ‌زنی معدنی
بهینه‌سازی فرآیند
الگوریتم ژنتیک
بهره‌وری انرژی
بهینه‌سازی فراابتکاری

چکیده

بهره‌وری انرژی و کنترل کیفیت محصول، به‌ویژه در چارچوب نوآورانه Mine 4.0، از دغدغه‌های اساسی در عملیات آسیاب‌های سنگ‌زنی هستند. این مطالعه یک چارچوب بهینه‌سازی مبتنی بر الگوریتم ژنتیک (GA) جدید را معرفی می‌کند که به‌طور خاص برای رسیدگی به این چالش‌ها توسعه داده شده است. با توجه به مصرف انرژی قابل توجه صنعت معدن، به‌ویژه در فرآیندهای سنگ‌زنی، رویکرد پیشنهادی پارامترهای کلیدی مانند ترکیب خوراک، نرخ جریان آب و سطح مصرف برق را بهینه می‌کند، در حالی که میزان سرریز شدن را نزدیک به آستانه هدف ۲۰٪ نگه می‌دارد. با استفاده از داده‌های عملیاتی واقعی از یک کارخانه مراکشی، GA به میانگین خطای مطلق 0.47 (MAE) دست یافت که از الگوریتم شبیه‌سازی تبرید (SA) و بهینه‌سازی ازدحام ذرات (PSO) که به ترتیب MAEهای ۱.۱۴ و ۰.۷۴ را به همراه داشتند، عملکرد بهتری داشت. GA همچنین پایداری و استحکام همگرایی برتر را نشان داد، همانطور که با تغییرپذیری کمتر در مصرف برق پیش‌بینی‌شده مشهود است. این نتایج، اثربخشی چارچوب GA را در پیمایش فضاهای پارامتری غیرخطی و با ابعاد بالا و بهبود بهره‌وری انرژی و در عین حال تضمین ثبات کیفیت محصول، تأیید می‌کند. در نهایت، این تحقیق پتانسیل بهینه‌سازی فراابتکاری را در افزایش راندمان آسیاب تأیید می‌کند و از تغییر گسترده‌تر به سمت عملیات معدنی هوشمند و پایدار تحت الگوی Mine 4.0 پشتیبانی می‌کند.

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