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Modeling and control of AG mill energy consumption based on ore hardness distribution in a large-scale iron ore plant

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ABSTRACT

The performance of autogenous (AG) grinding circuits is highly sensitive to variations in ore hardness, particularly in dry processing operations with limited buffering capacity. This study investigated on the influence of ore hardness variability on the operational behavior of the AG mill in Line 3 of the Gole-Gohar Iron Ore Concentration Plant. A total of 82 feed samples were collected and analyzed using the SAG Power Index (SPI) test to quantify ore hardness. The SPI results ranged from 48 to 236 minutes, revealing substantial heterogeneity in the run-of-mine feed. Correlation analyses demonstrated that increasing ore hardness resulted in reduced mill feed rate and increased specific energy consumption, primarily due to extended residence time and lower breakage efficiency. A linear regression model was developed to predict the mill's specific energy demand as a function of SPI, providing a practical tool for energy forecasting and operational optimization. Furthermore, hardness-based ore classification and blending strategies were designed to mitigate the adverse impact of hard feed on mill performance. These homogenization approaches, supported by block model data and SPI testing, offer a cost-effective means to enhance process stability and energy efficiency. Overall, the findings underscore the importance of incorporating quantitative hardness characterization into comminution circuit design, control systems, and mine-to-mill planning frameworks.

Keywords: *AG Mill; Modeling; SPI Test; Gole-gohar.*

1. Introduction

The performance of grinding mills and the overall efficiency of comminution equipment are significantly influenced by the quality of the large ore fragments. This dependency becomes particularly critical in autogenous (AG) and semi-autogenous (SAG) mills, where the ore itself acts as the primary grinding medium. Therefore, identifying and characterizing the properties of the ore, especially its hardness, is of ultimate importance [1]. Variations in ore properties especially hardness affect the performance of AG and SAG mills and result in significant instabilities in plant throughput and production. Consequently, a cost-effective and time-efficient method is needed to determine these properties and predict their impact on mill behavior and performance [2].Any changes in the feed rate, ore hardness, or particle size distribution of the mill feed can lead to deviations from steady-state operation. Among these factors, ore hardness and feed particle size distribution play vital roles in mill operation [3, 4]. Under typical conditions, an increase in feed rate leads to an increase in mill load volume and consequently in power draw. If ore hardness increases, the grinding rate decreases, resulting in a build-up of load inside the mill and a further increase in power draw. While power draw correlates directly with the internal mill load, there is no direct relation between feed rate and mill power consumption [5]. Numerous studies have aimed to develop accurate and practical methods for determining ore hardness with respect to sample quantity, test duration, cost, and precision. In 1994, Starkey and Dobie introduced the widely used SPI (SAG Power Index) test, which was found to be superior to existing methods. This test involves a series of grinding and screening stages within a laboratory-scale SAG mill (10.2 cm*30.5 cm) using a 2 kg ore sample. The test determines the time required (in minute) for reducing ore with an initial K80 of 12.7 mm to a product K80 of 1.7 mm, which is used as the index of ore hardness. Starkey also proposed the first empirical relation (equation 1) to calculate the industrial SAG mill power based on the SPI test [6]:

$$P_{SAG} = \left({d_{80p}}^{-0.33}\right)(2.2 + 0.1t) \tag{1}$$

where:

- P_{SAG} is the industrial SAG mill power (kWh/t),
- d_{80p} is the product particle size (μm),
- t is the SPI test time (min)

This relation has since been revised by several researchers to better different ore types and deposit conditions, including works by Kosick & Bennett (1999) [7], Akbarinasab et al. [8], Azimi et al. [9], Amelunxen et al. [10], Dehghani [11], Paymard [12], Jahani [13], and Asadi [14]. In 1999, Kosick and Bennett categorized ores into three geological structure groups (A, B, C) and evaluated power distribution in SAG mills for each group. SPI tests were conducted on samples from each zone. The zones with the highest sampling frequency exhibited the greatest variations. As even small fluctuations in mill power can lead to substantial changes in circuit capacity, knowledge of the ore hardness distribution is essential for reliable operation and design decisions. By accurately identifying hardness variations, it becomes possible to

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estimate the proportion of ore that can be effectively processed at the target throughput (equation 2) [7].

$$P_{SAG}\left(\text{kWh}/_{\text{t}}\right) = 0.0025T^2 - 0.0663T + 5.6358 \quad (2)$$

In 2014, Meysam Ghorbani Moghaddam conducted that due to the high sensitivity of AG mills to feed characteristics, 11 rounds of sampling campaigns were conducted from the feed, product, concentrate, and final dry tailings of the magnetic separation circuit, with sampling intervals of two hours. The SPI test was carried out to assess ore hardness. Through dimensional analysis of the feed in three campaigns, it was concluded that ore hardness had a more significant effect on AG mill performance than particle size distribution. Additionally, grade and recovery analyses revealed that increased ore hardness resulted in lower feed grade and reduced recovery, though the concentrate grade remained unaffected. As expected, increased ore hardness also led to finer product sizes and higher specific energy consumption [15]. In 2006, Mr. Azimi designed and built a laboratory-scale SAG mill at the Sarcheshmeh Copper Complex to determine the SPI. This study revealed that the model provided by Minnovex did not adequately predict power consumption in this case. A new empirical model tailored to the Sarcheshmeh SAG mill was developed using SPI tests and additional operational parameters, achieving a prediction error margin of only 2.5% (equation 3) [9]:

$$\mathrm{P}\left(\mathrm{Kwh}/_{\mathrm{t}}\right) = \mathrm{a.SPI^b} + \mathrm{c.}\,(\mathrm{k_{80}})^{\mathrm{d}} + \mathrm{f.}\left(\frac{\mathrm{H}}{1000}\right) + \mathrm{g.}\left(\frac{\mathrm{p}}{1000}\right) \quad (3)$$

where:

- SPI is the test time (minute),
- K_{80} is the product particle size (mm),
- H is the liner operation time (hour),
- p is the bearing pressure (kPa),
- and a, b, c, d, f, g are empirically determined constants.

Paymard (2007) optimized ball charge levels in the SAG mill at the Sarcheshmeh plant to reduce energy consumption and costs while increasing production [12]. In 2009, Dehghani evaluated the performance of the AG mill at the Se-chahoun-Choghart plant using SPI tests. A model was developed to estimate AG mill power based on test time (equation 4):

$$\text{AG Mill Power} = 7.098\ln(x) - 25.05 \quad (4)$$

However, equation 4 was only accurate for the Se-chahoun plant and did not yield acceptable results for Choghart due to differences in feed characteristics [11]. Jahani et al. (2011) compared the energy consumption and final product output of SAG and ball mills at the Sarcheshmeh Copper Complex. It was found that the ball mill consumed 10.7% more energy, while the SAG mill produced 10.76% more final product. In addition, the limitations in Azimi's SPI-based power model within the 100–200 SPI range was identified, where the effect of hardness on power consumption was negligible [13]. Amelunxen et al. (2014) revised the SPI test and developed the SGI (SAG Grindability Index) test to improve the accuracy of SAG power predictions. Based on their modifications, equation 5 was proposed [10]:

$$\text{Power}\left(\frac{\mathrm{Kwh}}{\mathrm{t}}\right) = 5.9 \times \left(\frac{\mathrm{SGI}}{\sqrt{\mathrm{P_{80}}}}\right)^{0.55} \times \mathrm{f_{SAG}} \quad (5)$$

where:

- SGI is the ore hardness index (minute),
- P_{80} is the product size (μm),
- f_SAG is a calibration factor (0.85 for pebble-crusher circuits, 0.90 for fine feed).

In 2017 Asadi investigated feed hardness and particle size distribution as part of a performance monitoring and troubleshooting study on the Sarcheshmeh SAG mill. Due to large fluctuations in feed hardness and particle size attributable to a sloped surge pile and varied feed sources SPI testing was used to develop recommendations for feed homogenization [14]. Namaei Roudi and Behnamfard in 2022 presented the development of empirical models to predict the power consumption of the autogenous (AG) mill at the Sangan Iron Ore Processing Plant, using operational and ore property parameters. The authors evaluated one, two, and four-parameter models, incorporating variables such as the SAG Power Index (SPI), product particle size (P80), trunnion pressure (p) and liner operating time (H). While one- and two-parameter models based on SPI and P80 yielded poor predictive accuracy, a four-parameter model significantly improved predictions when optimized using Excel's Solver Add-In to minimize error. The final model achieved an average relative error of 2.93% for training data and 2.39% for validation data, demonstrating its effectiveness for operational forecasting and energy optimization. The study emphasizes the importance of multi-variable empirical modeling over simplified approaches in accurately capturing AG mill energy behavior under real-world conditions [16].

Saldaña, et al. in 2023 investigated the optimization of a semi-autogenous grinding (SAG) process in a Chilean copper concentrator plant by applying statistical analysis and machine learning techniques. The authors developed predictive models using regression, decision trees (Random Forest, GBM, XGBoost), and artificial neural networks (ANNs), based on 27 months of operational data encompassing 12 variables such as mineral hardness, feed size, liner age, and rotational speed. Among the models, ANNs demonstrated the highest predictive accuracy (R^2=0.88). The optimized strategies included a mine-to-mill (M2M) approach that enhanced fragmentation and increased production by 4.42% while reducing energy consumption by 7.62%. Additionally, tuning mill parameters like rotational speed and solids concentration further improved performance and enabled energy savings of up to 5.85%. The study confirms the effectiveness of ML-driven digital models for enhancing throughput and energy efficiency in mineral comminution circuits [17]. Steady state operation of processing plant equipment is vital for maximizing productivity. At the Gole-gohar Iron Ore Concentration Plant, three AG mills form the processing bottleneck and are highly sensitive to feed variability, especially ore hardness [18]. This variability directly impacts production and poses economic risks. Given the significant hardness variation observed in the plant feed, the present study financially supported by Gol-gohar Mining and Industrial Company aimed to evaluate the relation between ore hardness and AG mill performance. Additionally, by mapping the hardness distribution across Mine No. 1, the required energy consumption in different mine zones was determined to facilitate optimized design, extraction, feeding, and homogenization strategies, thereby reducing process fluctuations.

2. Materials and methods

2.1. Plant description and sampling

In the Gole-Gohar processing circuit, the run-of-mine iron ore is first crushed by a gyratory crusher to a top size below 200 mm and subsequently directed to dry autogenous (AG) mills for further comminution, aiming to achieve adequate mineral liberation. When the particle size is reduced to approximately 450 μm, the ground product is subjected to dry magnetic separation, after which the final dry concentrate is obtained. A schematic view of the AG mill operating in Line 3 of the Gole-Gohar complex is shown in Figure 1.

The design and operating specifications of the AG mill used in the grinding circuit of the Gole-Gohar Iron Ore Concentration Plant are summarized in Table 1. As the primary throughput-limiting unit within the circuit, the AG mill has a critical impact on the overall process efficiency and plant productivity. Consequently, a systematic evaluation of the key influencing parameters—particularly the ore feed hardness, which governs mill load fluctuations and directly affects grinding stability—is essential. Understanding the interaction between feed characteristics and mill performance provides valuable insight into optimizing comminution efficiency and ensuring the stable operation of the entire processing circuit.

Figure 1. Autogenous mill in Line 3 of the Gole-gohar complex.

Table 1. Specifications of the Gole-gohar AG mill.

Parameter	Value
Mill length	12.2 meters
Mill diameter	9 meters
Throughput	400–800 tons per hour
Motor power	3000 kW
Rotational speed	12 rpm
Liner type	Manganese steel, wear-resistant
Feed size	< 200 mm
Product size (d_{80})	450 microns
Grinding media	Ore itself (autogenous grinding)
Manufacturer	Krupp Polysius

2.2. Sampling procedure

To evaluate the influence of ore hardness on the performance of the AG mill, representative feed samples were collected for hardness testing and subsequent analysis of the mill response to variations in feed competency. The sampling methodology was adapted, with minor modifications, from the procedures proposed by Starkey and Dobby (1996) [6], Akbarinasab (2003) [8], and Ghorbanimoghaddam (2014) [15]. Sampling was performed at the point of apron feeder of the AG mill conveyor in Line 3. At intervals of 30 seconds, several hand-sized rock fragments were randomly selected from the feeder. Half of the collected fragments were placed into one sample bag and the remaining half into another, continuing for approximately 20–30 minutes per sampling session.

Each session thus lasted about 30 minutes and produced two parallel samples, allowing for repeatability assessment and quality control. Sampling was carried out over 24 separate days, with each campaign lasting between 1 and 2 hours. The primary modification relative to previous studies involved increasing the sampling frequency, reducing the interval from 2 minutes to 30 seconds, thereby significantly enhancing the sample volume and statistical representativeness. The sampling procedure and the corresponding location are illustrated in Figure 2.

Figure 2. AG mill feed sampling at the apron feeder.

2.3. Sample Preparation and SPI Test

The feed samples (approximately 60–80 kg) were transported to Gole-gohar's semi-industrial laboratory. With coordination from the processing department, operational data of the AG mill at the time of sampling were obtained, including power consumption, feed rate, exhaust fan power, and pressure readings before and after the mill in 30-minute intervals. Samples were prepared according to the SPI (Sag Power Index). Each bulk sample was split into 2 kg subsamples for the SPI. In total, 82 samples were tested. The SPI results were then compared against the corresponding mill performance data. The testing procedure and equipment are illustrated in Figure 3.

Figure 3. SPI testing procedure and equipment.

2.4. Feed homogenization based on SPI test

Feed allocation to the Gole-Gohar processing plants has traditionally been based on the average ore grade, with limited consideration of feed hardness variability. However, incorporating ore hardness data into mine block models provides a valuable opportunity to design feed homogenization strategies that account for this influential parameter. The primary objective of this study was to determine the effective hardness of blended feeds composed of samples with different hardness levels and to define optimal mixing ratios capable of achieving a target composite hardness. Since ore hardness in this investigation was quantified using the SPI test, the same methodology was applied to estimate the hardness of the blended samples. Several blending scenarios were designed and experimentally evaluated, and the results were used to establish guidelines for future feed homogenization strategies based on ore's competency.

Given the observed sensitivity of AG mill performance to variations in feed hardness, it is crucial to maintain the feed within an acceptable hardness range to ensure stable operation and maximize comminution efficiency. Accordingly, developing a robust feed blending methodology is essential for achieving consistent mill throughput and energy efficiency.

In practice, the feed to the plant is typically derived from multiple active mining faces, each characterized by distinct hardness values and production tonnages. By quantifying both the hardness and tonnage contribution of each source, the overall hardness of the composite feed can be estimated using a weighted-average approach. This estimation, when combined with established relationships between ore hardness, mill throughput, and specific energy consumption, enables reliable prediction of mill performance with minimal testing effort and cost. Such predictive capability is instrumental in stabilizing plant operation, reducing process fluctuations, and improving overall production planning.

Figure 4 illustrates two representative ore samples with distinctly different hardness values that were blended to generate a composite sample used for hardness testing.

Figure 4. Representative ore samples with different hardness values.

Four blending scenarios were designed to evaluate the effect of feed composition on the resulting ore hardness and to explore practical strategies for feed homogenization. In each scenario, samples with distinct SPI values were combined according to predefined ratios, after which representative subsamples were extracted from the blended material. From each composite, a 2 kg sample was prepared and subjected to SPI testing in accordance with standard procedures. The tested blending scenarios were defined as follows:

- Case 1: Equal blending of two samples with different hardness levels (1:1 ratio)
- Case 2: 70% harder sample + 30% softer sample
- Case 3: 70% softer sample + 30% harder sample
- Case 4: Equal blending of three samples with different hardness levels (1:1:1 ratio)

Each scenario was tested using multiple sets of samples with varying hardness values to capture a representative range of operational conditions. In cases where certain samples exhibited exceptionally high hardness—posing a potential risk of reduced mill throughput and operational instability—feed homogenization was applied as a strategy in order to mitigate these effects prior to plant delivery. These blending approaches provide practical guidelines for minimizing the impact of hard ore on mill performance and for achieving better control over feed variability. The results emphasize that proper feed composition and homogenization can significantly contribute to stable AG mill operation and consistent comminution efficiency.

3. Result and Discussion

3.1. Effect of Ore Hardness on AG Mill Performance

Feed samples were collected from the autogenous (AG) mill of Line 3, and their hardness was determined using the SAG Power Index (SPI) test, accompanied by simultaneous recording of mill operating parameters. To verify the accuracy of both sampling and hardness testing procedures, duplicate samples were taken for each time interval. Among the 15 duplicate SPI tests, the differences between replicates were negligible, confirming the reliability of the sampling protocol. Accordingly, the average value of each pair was considered representative of feed hardness. For subsequent samples, only a single SPI test was performed per interval, given the validated repeatability of the method. In total, 82 feed samples were analyzed over 24 days of mill operation. The results revealed a wide range of ore hardness values, which had a pronounced impact on mill performance. SPI values varied from a minimum of 48 minutes (softest sample) to a maximum of 236 minutes (hardest sample), with an average of approximately 126 minutes. Consistent with earlier investigations on the orebody and mill feed, the data confirm a significant increase in feed hardness over time, along with a broad distribution indicative of considerable variability in ore properties.

Ore hardness was found to exert a strong influence on AG mill behavior, affecting feed rate, power draw, mill load, exhaust fan power, and discharge pressure. These fluctuations led to instability in mill operation under varying hardness conditions. The control system of Line 3 maintains the mill power draw near 2000 kW by automatically adjusting the feed rate: when power exceeds the target, the feed rate decreases, and vice versa. Consequently, the mill rarely operates under steady-state conditions; harder feed reduces throughput to maintain constant power, while softer feed allows higher throughput. Predicting the power required to process variable ore types is therefore essential for reducing operational fluctuations and improving performance. Among the governing parameters, ore hardness and feed size are the most significant. As established in previous studies, feed size tends to correlate with hardness, since harder ores are generally coarser. Hence, by quantifying feed hardness, the specific energy consumption of the AG mill can be estimated with reasonable accuracy. Because the feed rate is modulated to maintain nearly constant power, this analysis focuses on specific energy consumption rather than absolute power.

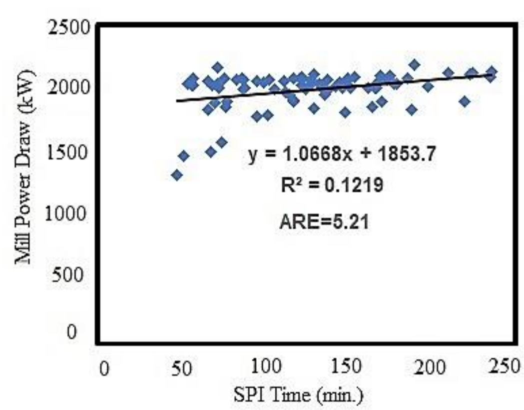

Figure 5. Relation between feed hardness and mill power draw.

Figure 5 illustrates the relationship between feed hardness and mill power draw. Despite fluctuations, power draw remains close to 2000 kW, with a slight upward trend reflecting the greater energy demand of harder ores. The corresponding relationships between ore hardness and both feed rate and specific energy consumption are presented in Figures 6 and 7, respectively.

As shown in Figure 6, the feed rate decreases systematically with increasing hardness. This behavior arises because harder ores require more energy for breakage, shifting the dominant mechanism from impact to abrasion, which involves longer residence time. Consequently, lower feed rates are necessary to achieve adequate grinding of harder materials. In turn, prolonged residence time results in reduced breakage rate and lower throughput. The strong correlations evident in these figures confirm that ore hardness is a reliable predictor of mill performance.

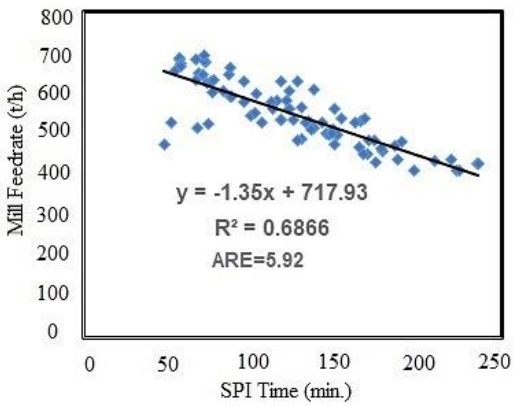

Figure 6. Relation between feed hardness and mill feed rate.

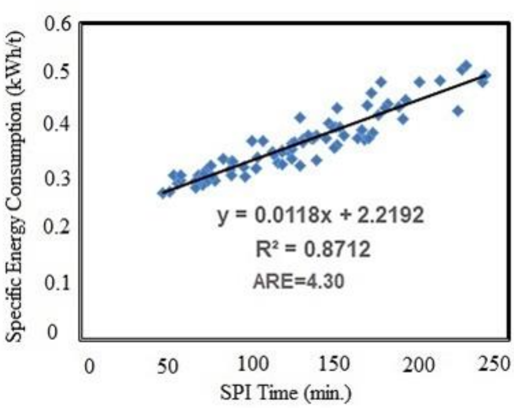

Figure 7. Relation between feed hardness and specific energy consumption.

A quantitative relationship was developed to estimate specific energy consumption based on SPI test results and operating data (equation 6):

$$Specific\ Energy\left(\mathrm{kWh}/_{\mathrm{t}}\right) = 0.0118 * \mathrm{SPI}(min) + 2.2192 \quad (6)$$

This regression model (R^2=0.87) enables accurate estimation of specific energy consumption from SPI values at minimal cost, supporting proactive feed blending and mill optimization strategies. According to the model and the orebody hardness distribution, approximately 52% of the orebody has SPI<50 minutes (requiring <2.81 kWh/t), 26% lies between 50–100 minutes (2.81–3.40 kWh/t), and 22% exceeds 100 minutes (>3.40 kWh/t). Based on these findings, the orebody was divided into hardness zones according to specific energy requirements, facilitating improved mine scheduling, feed blending, and overall plant efficiency.

To evaluate the performance of the developed linear SPI–specific energy model (equation 6), its predictive accuracy was compared with alternative approaches and with models reported in the literature. Empirical models derived from previous studies, such as those proposed by Starkey and Dobby (1996) and Amelunxen et al. (2013), relating SPI or SAG Power Index equivalents to specific energy consumption through linear or power-law correlations. When applied to the present dataset, these published correlations yielded coefficients of determination (R^2) between 0.62 and 0.78, lower than that of the proposed model (R^2=0.87). The validity of model assessed by the Average Relative Error (ARE) function also, is as follows (equation 7):

$$ARE = \frac{100\sum\left|\frac{W_{real}-W_{model}}{W_{real}}\right|}{n} \quad (7)$$

where, ARE (%) is the percentage of the model error, W_{real} and W_{model} are real and redicated mill specific energy consumption, and n (=82) is the number of measurements made [4, 16]. The ARE error values of developed model (equation 6) alongside models that were structurally similar to ours, are summarized in Table 2.

Table 2. Comparison of the ARE error values of developed model and the alternative models.

Model Type	ARE (%)	Reference
Equation 2	98.44	Kosick and Bennett [7]
Equation 4	53.59	Dehghani [11]
Equation 6	4.30	Developed model

As observed in the Table 2, a significant discrepancy exists between the values for the developed model and those of the other models. This difference further underscores the validity of the developed model. The improved performance can be attributed to the site-specific calibration of the model using operational data directly obtained from Line 3 of the Gole-Gohar plant, thereby better capturing local ore characteristics and mill behavior.

Alternative regression techniques, including polynomial fitting and multiple linear regression incorporating feed size and mill load as additional variables, were also tested. However, these approaches did not significantly improve model accuracy (R^2<0.88) and increased computational complexity without notable predictive gains. Hence, the linear model offers an optimal balance between simplicity, interpretability, and predictive reliability for practical plant applications.

3.2. Effect of ore hardness on exhaust fan power and mill pressure

In addition to power draw and feed rate, operating data for mill input/output pressures and exhaust fan power were collected during the sampling campaign (Figures 8 and 9). Since the Line 3 AG mill operates under dry conditions, discharge of material is assisted by an airstream generated by the downstream exhaust fan.

Beyond its influence on throughput and energy consumption, ore hardness variation also affects the auxiliary systems of the autogenous grinding (AG) circuit, particularly the exhaust fan power and mill pressure dynamics. Since the Line 3 AG mill operates under dry conditions, material transport and discharge rely heavily on airflow generated by the downstream exhaust fan. Variations in ore hardness and consequently in mill load and residence time induce measurable fluctuations in the internal pressure profile of the system. As hardness increases, the mill experiences greater material hold-up and reduced discharge rates. This accumulation elevates the inlet (suction) pressure, while the outlet pressure tends to decline slightly due to restricted airflow through the material bed. The exhaust fan compensates by drawing higher power to maintain adequate airflow, which was observed as a marginal but consistent increase in fan power with increasing SPI. Although these changes are relatively small compared to the variations in mill power draw, they indicate that ore hardness indirectly influences the performance and energy demand of the air-handling system. From an operational standpoint, understanding these secondary effects is important for maintaining circuit stability and ensuring effective material transport. Prolonged operation under high-hardness feed conditions can impose additional load on the exhaust fan and potentially alter the pressure balance required for efficient discharge. This, in turn, can influence dust entrainment, classification efficiency, and even product moisture controls all critical parameters in dry grinding environments. Therefore, while the primary operational adjustments are made through feed rate modulation to stabilize mill power, secondary systems such as air circulation and pressure control also respond dynamically to hardness-induced fluctuations. Monitoring these parameters alongside SPI-based hardness predictions could enhance process diagnostics and enable early detection of potential bottlenecks or inefficiencies. Future work should explore integrated control strategies that couple mill power regulation with adaptive airflow management, allowing simultaneous optimization of energy use and material transport efficiency under variable feed conditions.

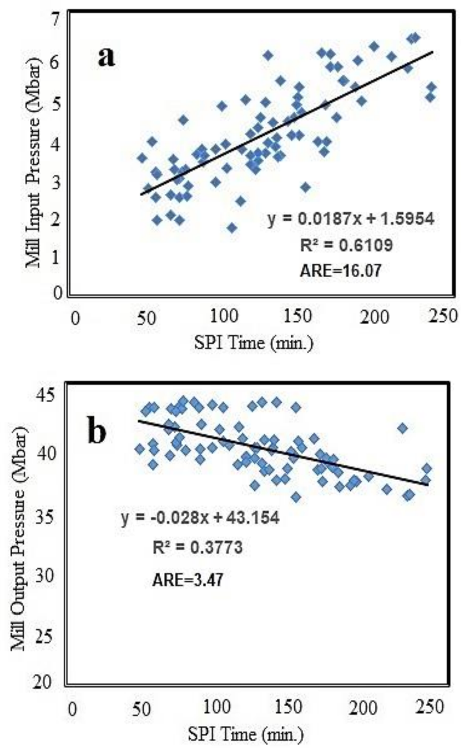

Figure 8. Relation between feed hardness and mill input and output pressure.

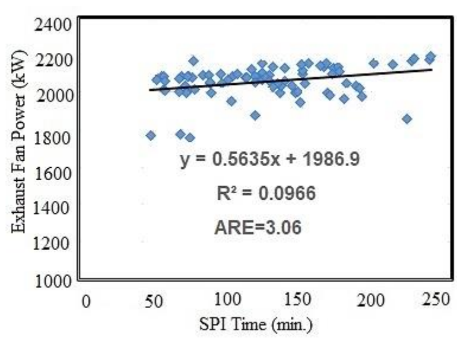

Figure 9. Relation between feed hardness and exhaust fan power.

4. Conclusion

The effect of ore hardness variability on the performance of dry autogenous grinding (AG) circuits at the Gole-gohar Iron Ore Concentration Plant was evaluated. Through comprehensive sampling, SPI testing, and mill performance monitoring, it was demonstrated that feed hardness is the primary driver of mill throughput, specific energy consumption, and operational stability. SPI values obtained from 82 samples ranged widely from 48 to 236 minutes, reflecting substantial heterogeneity in the run-of-mine ore. This variation was shown to directly influence the mill's dynamic response, as higher SPI values indicative of harder ore necessitated reduced feed rates to maintain a relatively constant power draw. The transition in dominant breakage mechanisms from impact to abrasion under harder feed conditions increased energy requirements and reduced processing efficiency. A predictive model with R^2=0.87, ARE of 4.30 was developed to estimate the specific energy consumption as a linear function of SPI, enabling accurate, low-cost energy forecasting across the orebody. This modeling capability, combined with spatial hardness mapping from the mine block model, facilitated the classification of the deposit into operational hardness zones. Furthermore, hardness-based blending strategies were designed and validated, demonstrating their effectiveness in moderating feed hardness variability prior to mill entry. These findings underscore the critical importance of incorporating ore hardness profiling into process control frameworks and mine-to-mill optimization programs. By integrating hardness data into feed scheduling and homogenization protocols, significant improvements in circuit stability, energy efficiency, and throughput consistency can be achieved. The study highlights the necessity of adopting predictive hardness-based operational strategies, particularly in high-throughput, dry grinding circuits where buffer capacity is inherently limited. Future research may benefit from real-time hardness sensing and adaptive control systems to further optimize AG mill performance under variable geological conditions.

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