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Analysis of Ore Variability Influence on Comminution Energy Efficiency

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Abstract

Given the increasing concerns about the adverse effects attributable to climate change, two imperatives of the sustainability paradigm are to reduce pollution and CO_2 footprint, especially in the energy-intensive mining, mineral processing and beneficiation sectors of industry. Thus, a major challenge in minerals processing is to optimize the energy consumption of unit operations. In principle, this requires the utilization of all data and information that fully characterize the dynamics of all material and physical elements which constitute the organization that operates an ore crushing and screening process. By analyzing available data and information, this paper highlights how the variability in ore quality influences the energy of crushing and screening operations in a case study comminution facility. The empirical findings reinforce the need to apply robust models based on implementation of 4IR technologies to provide better information for decision making; in this case, towards continuous optimization of energy consumption to lower pollution and the CO_2 footprint of comminution unit operations.

Keywords
Data Analytics, Comminution Optimization, Energy Efficiency, CO_2 reduction, Operations Management

1.Introduction

A pragmatic approach to dealing with increasing concerns about the adverse effects attributable to climate change is to reduce pollution and the CO_2 footprint of industrial activities, especially in energy intensive mining and mineral processing operations. Iron ore mining is typically characterized by hard rock and the mining process creates pollution in the environment and ecology. The hard rock has to be comminuted (re: Dixit et al. 2018) in order to extract the mineral content from the run-of-mine (ROM). The collateral pollution arising from the comminution facilities represents a complementary issue to the challenge of CO_2 footprint.

The aforementioned complimentary issue to the challenge of CO_2 footprint in hard rock mining operations is attributed to the dry crushing and screening comminution processes that produces excessive quantities of dust pollution that is released to the immediate environment due to processing variable paramagnetic ore which further contributes to poor crusher energy efficiency. Kameristaya and Basamykina (2021) defines crusher energy efficiency as the utilization of less energy for the same activity to achieve similar output. It is important to note that crusher energy efficiency and comminution energy efficiency terms are used interchangeably in this report.

Although comminution facilities are typically established taking into consideration the nature of the ore (Connelly 2013), however, a primary challenge is to continuously optimize energy consumption coupled with reduction in CO_2 footprint during minerals processing operations. In the processing of ROM ore, the effectiveness of operations strongly depends on the energy efficiency of crushing. Crushing is foremost to ore comminution unit operations and contributes significantly to mining operational costs, pollution and CO_2 footprint. The energy consumption of a comminution facility is influenced by factors such as the type of crusher design and the type of run-of-mine (ROM) material processed through the crushing circuit (Napier-Munn 2005). Thus, it is important to invest in methods that improve the energy efficiency of crushers concurrently with reducing and minimizing operational costs, pollution, and CO_2 footprint during minerals processing operations.

Curiously, the continuous variability in ROM ore is often taken for granted in programs that seek to optimize the energy efficiency of crushers in comminution facilities. With a focus on the crushing process, the case study discussed in this paper examines how the continuous variability in ROM ore influences energy efficiency of a comminution facility. The research study objective is outlined in section 2, the literature review is briefly articulated in the following section 3. The research methodology is briefly described in section 4. The historical research data is briefly highlighted in section 5. The empirical observations are also briefly described in section 6, while some concluding remarks are provided in section 7. Some of the relevant references are listed in section 8 of the paper.

1.0 Research objective

The objective of the study was to determine, from historical data, how variabilities in iron ore assay influence comminution energy efficiency in an existing minerals processing operation. The following hypotheses were tested (see also Figure 2), viz -
H1: ROM moisture: Wet ROM will reduce the comminution energy efficiency of the crusher,
H2: ROM Fragmentation: Pre-processed ROM will improve the comminution energy efficiency of the crusher,
H3: ROM Fe (assay): Pre-blended ROM will improve the comminution energy efficiency of the crusher.

2.0 Literature Review

3.1 Ore Quality Characteristics' Impact on Comminution Processes

Interestingly, more than 60% of global iron reserves are in banded formations which contain alternating iron-rich layers of oxides and silicates. The iron-rich layers consist of mixtures of the various types of ore that require different mineral processing routes to achieve the desired beneficiation objectives (Kapadia 2018; Lagoeiro 2004). As the mining operation progresses, often from high-grade to low-grade ores, there is increase in the energy required to liberate the desired mineral content from impurities. According to Jankovic (2022), the comminution energy to liberate the ferromagnetic magnetite from the silica matrix could be over 30 kWh/t, an order of magnitude higher than the energy required to liberate paramagnetic hematite from oxide ores. Furthermore, deteriorating ore quality not only result in worsening pollution during mining operations, but also, increasing assay variabilities adversely impact on the energy efficiency of the comminution processes (Batterham and Bearman 2005), further worsening the CO_2 footprint during minerals processing and beneficiation.

As illustrated in Figure 1 (ref: Jankovic 2022), iron ore comminution comprises energy-intensive, upstream operations that are fundamental to minerals processing and beneficiation (Tromans 2008). In particular, ore crushing and screening may occur through several stages of the comminution processes, therefore, it is necessary to implement cost-effective methods to optimize energy consumption and to minimize pollution and the CO_2 footprint of comminution (Napier-Munn 2005). In essence, the variabilities in ore grades mean that the comminution processes must be continuously monitored and optimized to improve energy efficiency, minimize pollution and reduce CO_2 footprint (Sharma et al. 2010).

Types of Iron Ore Deposits

Hematite (Ferromagnetic) iron ore chemical qualities are known to deteriorate with depth from the surface, the greater the depth of the ore, the lower the grade Fe content. Conversely, the lower the Fe content, the higher the higher the impurities referred to as contaminants known as silicates. Hematite iron ore mined at greater depths from the earth's are diluted with some silicates that have been observed to negatively impact the dry crushing and screening comminution facilities process due to ore quality variabilities (McVeigh 1980).

Crusher Performance Optimization Models

Some of the literature review notes that there are system bottlenecks in comminution facilities and such bottlenecks are attributed to the crusher energy efficiencies. As noted by Airikka (2015), the crusher equipment are easily manipulated to supplement production efficiency at the expense of energy efficiency and associated CO_2 footprint. Airikka (2015) conducted a study in a comminution facility and developed a model crusher performance optimization model called the feed-forward control principle, the principle model recommended the utilization of an online instantaneous sensor to measure material propagation through the crushing circuit, and report any changes on the material height in the crusher bin. Given that such technology exists, it paves a way for advanced cost-effective methods for industrial 4IR technology applications in comminution energy efficiency optimization and the potential reduction of the associated CO_2 footprint.

Issues in Iron Ore Comminution

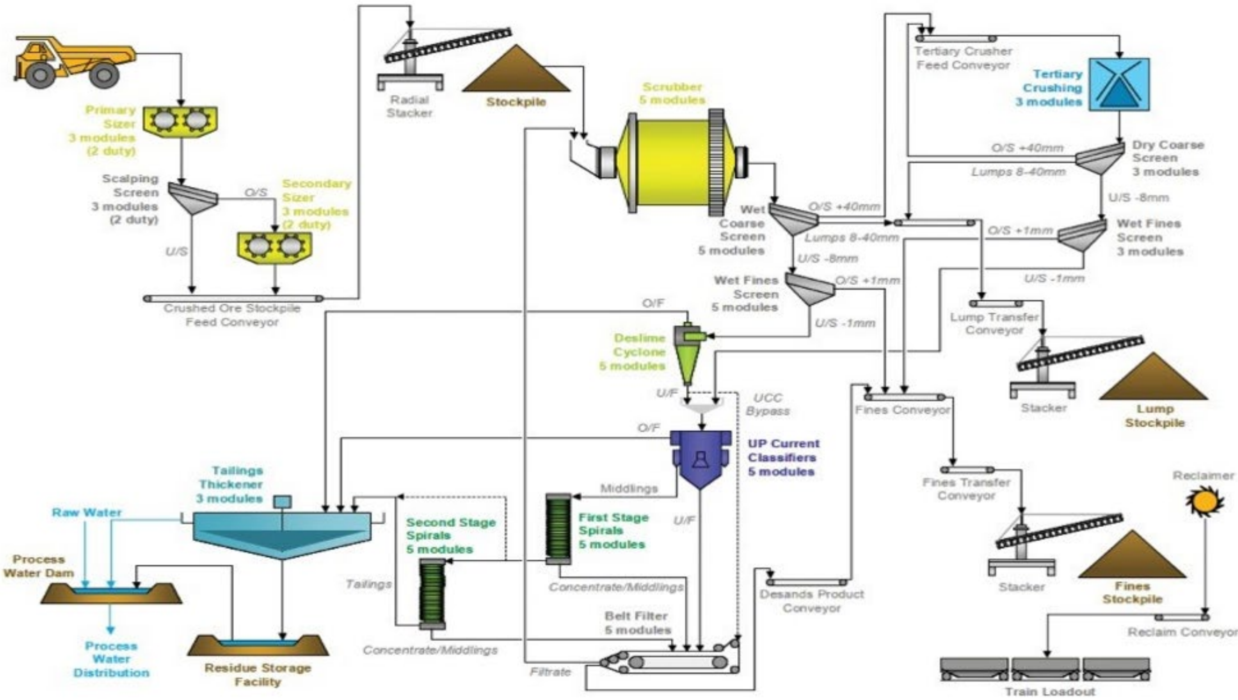

Figure 1. Comminution facilities in iron ore minerals processing
[source: Jankovic (2022)**]**

In the processing of ore extracted from banded iron formations, comminution unit operations generally encounter ore variability challenges as discussed in more technical detail (in e.g., Gomes et al. 2013; and Jankovic (2022)). A study by Yamashita et al. (2021) noted that ore quality variables such as ROM moisture are part of a broader range of what is known as disturbance parameters which are classified as exogenous signals that negatively impact the crushing process; these exogenous signals can be measured but cannot necessarily be manipulated by plant operators. However, if they were to be manipulated, it would demand a great deal of effort to understand their magnitude and frequency of impact. Therefore, it is important to highlight that as much as these variables cannot be manipulated given the type of distinct operational designs of comminution processes, it is expected that plant operator can minimize the negative impacts caused by such of disturbances in the comminution process.

Airikka (2015) points out that the lack of plant-wide process control through several stages of ore crushing and screening limits smooth regulation of process variables in comminution facilities. From a management viewpoint, Ras and Visser (2015) have classified some of the challenges in terms of: (i) constraints in energy, labour and production capacity; (ii) capital intensive challenges such as plant retro-fitment modifications that can be very expensive to install, maintain and operate; (iii) continuous improvement challenges attributable to intermittent operations; and (iv) compressed market, that is, a highly constrained and competitive commodity market. The foremost management concern is how to resolve the energy related constraints of efficiency, pollution, and CO_2 footprint.

Some studies (see, for example, Tromans 2008; Fuerstenau and Abouzeid 2002) tend to focus on how to optimize technical efficiency of fracture mechanics and crack propagation processes associated with minerals comminution. The focus on technical efficiency of fracture mechanics and crack propagation in order to obtain optimal particle sizes relates more to the design of energy-efficient milling machines. Subsequently, the approach in this paper is similar to that described in Góralczyk et al. (2020) where "process optimization with dedicated models and control systems is the most preferable solution for energy consumption reduction." The modelling and control systems approach are predicated on the collection, collation, analyses and syntheses of data and information arising from both the internal dynamics of the comminution processes and the externalities surrounding comminution unit operations. It is in this regard that the remainder of the discourse briefly describes an empirical examination of how the variabilities in ore assay influence the crusher power factor in a case study comminution facility.

3.0 Research Methodology

This research study is aimed at analyzing the impact of variable ore qualities on comminution energy efficiency through the analysis of existing historical data in guideline with the literature reviewed as documented and published empirical results of existing crusher production optimization methods. It thus suffices to conclude that this research study is suited to be conducted as an analytical research study.

4.0 Research Data

Table 1 shows the historical research data that is a time series data that collected continuously over a specific period by means of crusher feed sensors and instant online chemical analysis tool called a "Geoscan", these primary data acquisition tools record the following signals; Date, hourly tons, Fe, SiO2, Al2O3, K2O, S, P, Mn, H_2O and Primary crusher power draws (kWh/t).

Table 1. Example of the historical research data.

Time	Fe	Tonnes	Crusher Power Draw	H2O	Pre-processed ROM	Crusher Power Factors	SiO2	Al2O3	K2O	Mn	P	S
01 01 2022	62,14	47 443	289,03	42,28		0,85	5,66	1,56	0,18	0,03	0,06	0,07
02 01 2022	64,04	48 828	259,37	38,38		0,87	4,97	1,21	0,17	0,03	0,04	0,07
03 01 2022	62,98	29 792	171,14	39,87		0,80	4,45	1,91	0,18	0,04	0,06	0,07
04 01 2022	61,74	33 122	289,74	40,59		0,82	4,51	1,48	0,11	0,15	0,08	0,07
05 01 2022	62,27	33 292	259,26	40,87		0,77	4,64	1,41	0,11	0,09	0,07	0,07
06 01 2022	62,80	33 462	171,29	41,16		0,75	4,77	1,35	0,11	0,03	0,05	0,06
07 01 2022	62,06	21 394	262,79	44,92		0,85	4,43	1,23	0,13	0,06	0,05	0,06
08 01 2022	55,94	23 595	241,18	38,87		0,81	5,57	1,56	0,17	0,04	0,05	0,06
09 01 2022	49,77	20 235	165,04	29,42		0,73	3,70	1,36	0,12	0,03	0,04	0,05
10 01 2022	54,57	12 427	209,62	33,52		0,79	4,93	1,19	0,14	0,06	0,03	0,05
11 01 2022	55,04	13 058	207,93	24,12		0,42	4,36	1,31	0,13	0,05	0,04	0,05
12 01 2022	56,58	13 690	207,93	18,09		0,35	4,24	1,36	0,13	0,04	0,04	0,06
13 01 2022	58,13	10 101	207,93	12,06		0,35	4,13	1,41	0,13	0,04	0,04	0,06
14 01 2022	59,68	8 623	206,23	6,03		0,70	4,01	1,46	0,13	0,04	0,04	0,06
15 01 2022	61,22	7 144	222,20			0,61	3,89	1,51	0,12	0,04	0,04	0,06
16 01 2022	63,78	40 099	238,17			0,82	4,80	1,19	0,15	0,03	0,06	0,07
17 01 2022	61,18	40 464	217,29			0,85	4,75	1,62	0,11	0,14	0,05	0,07
18 01 2022	64,00	32 155	212,77		97%	0,82	4,77	1,78	0,10	0,06	0,04	0,07
19 01 2022	56,94	29 356	112,96		80%	0,82	4,51	1,84	0,14	0,06	0,04	0,06
20 01 2022	59,59	27 782	222,39		0%	0,80	3,66	2,17	0,10	0,05	0,04	0,06
21 01 2022	59,87	35 311	300,07		3%	0,77	4,92	1,79	0,10	0,03	0,04	0,06
22 01 2022	63,98	49 392	281,52			0,84	4,83	5,81	0,11	0,03	0,05	0,07
23 01 2022	62,16	41 837	260,07			0,85	5,06	1,56	0,11	0,03	0,04	0,07
24 01 2022	62,48	30 687	302,46			0,79	5,39	1,58	0,12	0,04	0,06	0,07
25 01 2022	63,73	41 326	269,38			0,75	5,03	1,64	0,15	0,06	0,05	0,06
26 01 2022	63,78	40 353	297,57			0,83	3,89	1,50	0,15	0,07	0,05	0,07
27 01 2022	62,25	40 318	299,22			0,83	5,63	1,67	0,05	0,05	0,05	0,07
28 01 2022	63,34	39 611	252,13			0,85	5,57	1,64	0,10	0,03	0,03	0,07
29 01 2022	63,03	40 568	260,22			0,82	5,88	1,75	0,10	0,03	0,04	0,07
30 01 2022	59,64	36 341	225,09		12%	0,84	4,73	1,62	0,09	0,03	0,04	0,06
31 01 2022	51,66	11 593	282,03			0,76	3,23	1,23	0,09	0,03	0,03	0,06
01 02 2022	55,34	5 474	241,92			0,51	4,81	1,63	0,07	0,02	0,06	0,07
02 02 2022	53,91	11 708	201,81	8	31%	0,58	4,79	1,33	0,04	0,10	0,03	0,06
03 02 2022	63,52	31 401	161,35	20	92%	0,69	5,07	1,53	0,11	0,06	0,04	0,07
04 02 2022	62,96	31 810	245,45		73%	0,74	4,72	1,23	0,09	0,05	0,03	0,07
05 02 2022	64,05	43 869	199,05		0%	0,83	4,99	1,43	0,09	0,05	0,04	0,07
06 02 2022	63,82	34 940	229,36	8	9%	0,84	5,24	1,51	0,06	0,06	0,04	0,07
07 02 2022	61,01	13 300	166,83		22%	0,72	5,18	2,05	0,10	0,05	0,05	0,07
08 02 2022	60,53	3 133	237,20		9%	0,42	5,42	1,74	0,02	0,06	0,03	0,06
09 02 2022	62,81	32 636	177,65		4%	0,81	5,80	1,93	0,18	0,04	0,04	0,07
10 02 2022	63,33	42 390	305,91		73%	0,85	5,69	2,07	0,12	0,04	0,04	0,07
11 02 2022	61,38	12 072	272,80		8%	0,82	4,43	1,89	0,08	0,07	0,04	0,06
12 02 2022	64,16	32 645	239,70		34%	0,83	4,82	1,69	0,10	0,07	0,04	0,07
13 02 2022	52,75	11 434	206,60		99%	0,79	4,45	1,37	0,07	0,06	0,06	0,05
14 02 2022	58,09	20 841	173,50		44%	0,69	4,20	1,37	0,11	0,07	0,04	0,06
15 02 2022	63,43	13 277	261,70	44		0,65	5,57	1,82	0,12	0,04	0,04	0,07
16 02 2022	62,84	24 390	217,50		10%	0,66	3,49	1,18	0,10	0,05	0,04	0,07
18 02 2022	62,70	43 122	242,61			0,55	6,20	1,63	0,16	0,04	0,06	0,07
19 02 2022	63,74	47 079	302,57			0,72	5,30	1,59	0,11	0,04	0,03	0,07
20 02 2022	62,38	34 176	273,25			0,86	5,10	1,20	0,11	0,09	0,05	0,07
21 02 2022	62,75	47 759	285,05			0,80	6,50	1,33	0,08	0,06	0,04	0,07
22 02 2022	62,50	38 004	306,17			0,86	4,64	1,26	0,08	0,04	0,05	0,07
23 02 2022	63,46	49 368	263,82			0,83	5,59	1,49	0,08	0,06	0,04	0,07
24 02 2022	63,67	39 438	305,75		21%	0,86	3,89	1,20	0,15	0,05	0,11	0,07
25 02 2022	64,03	38 254	280,56			0,85	4,57	1,32	0,16	0,06	0,05	0,07
26 02 2022	55,67	26 458	261,38			0,82	3,93	1,03	0,12	0,04	0,04	0,06
27 02 2022	64,10	42 340	248,03			0,77	4,78	1,56	0,09	0,07	0,04	0,07
28 02 2022	60,90	31 037	142,39	15	7%	0,85	6,49	1,69	0,10	0,08	0,04	0,07
01 03 2022	63,64	45 535	248,29		1%	0,82	5,12	1,78	0,13	0,07	0,05	0,07
02 03 2022	63,68	37 137	309,74		30%	0,84	4,73	1,49	0,14	0,05	0,05	0,07

Correlation Statistics

Correlation statistics method is used to statistically compare variables to determine the extent to which they relate, statistical correlation is determined as the simplest way of comparing two or more variables in which there can either be a positive correlation where one variable increases with the other, or a negative correlation is where one variable increases with a decrease on the other (Williams et al. 2004).

Descriptive Statistics

Descriptive statistical analysis will improve the readers' understanding of the data collected and used for the research study, in this research study, the collected historical research data is described statistically to highlight statistical aspects such as medians, frequencies, mean, standard deviation, min-max values and the range.

Table 2. Summary of the research data descriptive statistical analysis

Column1	Pre-processed ROM Feed	ROM Moisture	ROM Fe	Crusher Feed Tons	Crusher Power Factor
Median	22	47	64	2294	0,78
Mean	27	49	64	2198	0,78
Std. Dev.	23	9	1	524	0,09
Std. Err.	**3**	**0**	**0**	**7**	**0,01**
Min.	0	29	56	1001	0,72
Max.	97	100	67	2984	0,85
Range	97	71	10	1983	0,13

Pearson Correlation Analysis Test Method

The Pearson's correlation test is used to determine a linear relationship between two variables and numerical values are assigned between -1 and 1, where -1 indicates a strong negative correlation between two variables, while a 1 indicates a strong positive correlation between two variables and 0 indicates no correlation between two variables (Nowicki 2008). Furthermore, the collected historical sample research data is ranked and a comprehensive two-tailed t-test calculation is used to determine the statistical significance of the data referred to as probability (ρ) and where ρ-value < .05 (alpha), the variable data has a statistical significance, and the more the ρ-value approaches 0 the higher the statistical significance (Okpala 2020).

Spearman Correlation Analysis Test Method

The Spearman correlation test is also statistical method that is used to determine a linear relationship between two variables when the data has prominent set of outliers, the Spearman rho correlation is applied to non-parametric continuous data, a correlation coefficient (r) numerical value is assigned between -1 and 1, where a negative r-value denotes a negative correlation and positive r-value denotes a positive correlation (Nowicki 2008).

Table 3. Summary of the research data correlation analysis

Crusher Power Factor	Pre-processed ROM Feed	ROM Moisture	ROM Fe	Crusher Feed Tons
ρ-value	<,001	<,001	<,001	<,001
	Statistical Significance	Statistical Significance	Statistical Significance	Statistical Significance
Correlation Coefficient (r)	0,09	0,21	0,02	0,06
	Positive Correlation	Positive Correlation	Positive Correlation	Positive Correlation

5.0 Empirical Study

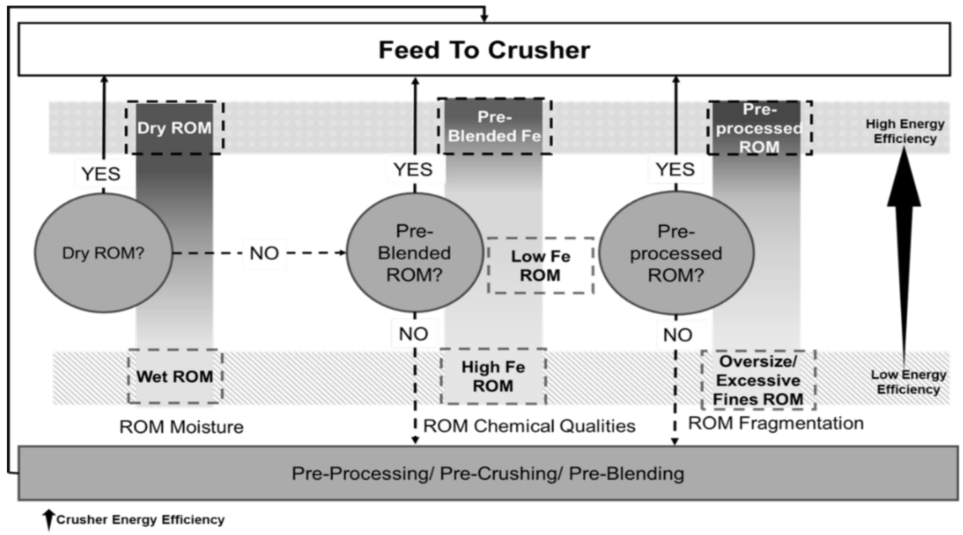

Figure 2. Conceptual model for the empirical study

At the case study plant, it is understood that the composition of the ore is monitored throughout the comminution process via an online instantaneous scanner and corroborated against physical samples analyzed in the in-house laboratory. It was observed that the time series data included records of the hourly tonnage milled, primary crusher power consumption, crusher power factor, as well as measurements of the composition of the ROM ore (i.e., Fe, SiO_2, Al_2O_3, K_2O, S, P, Mn, H_2O), and the ore particle size distribution (PSD). From data made available, the relationship between crusher power factor and ROM feed rate, ROM moisture content, ROM Fe, and pre-processed ROM (PSD) are respectively depicted in the four graphs in Figure 3.

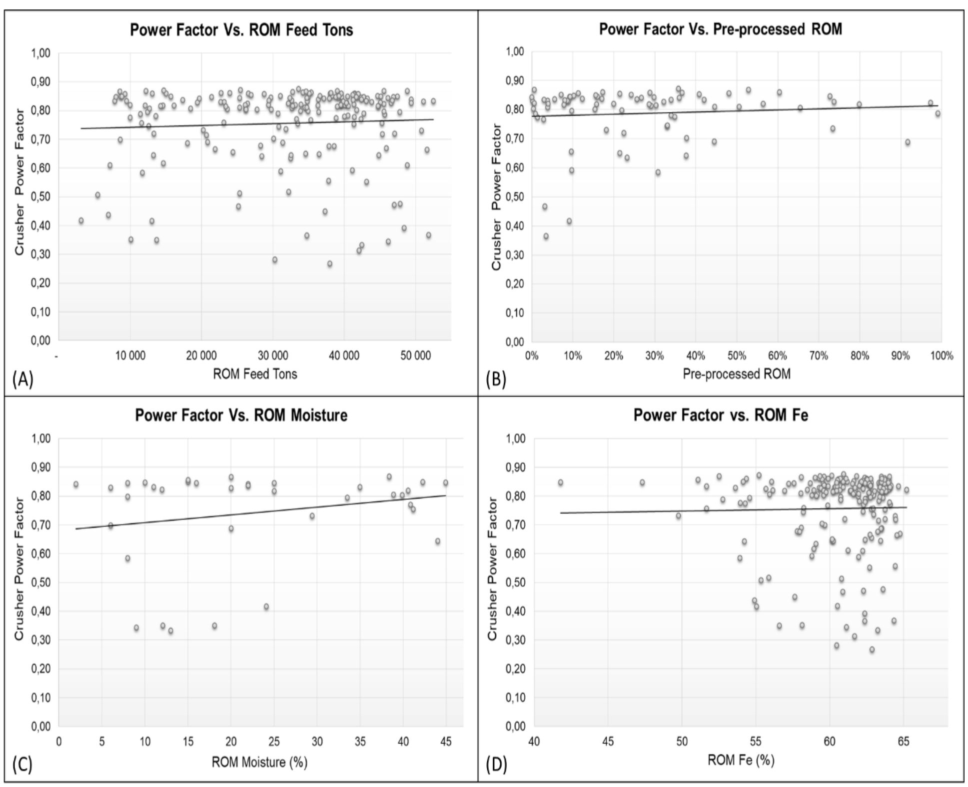

Figure 3. Influence of ROM variabilities on crusher power factor

As depicted in graph A of Figure 3, the historical data reveals significant levels of variance in the relationship between the ROM feed rate and the primary crusher power factor. Notwithstanding that there might be other exogenous influences, it is reasonable to assume that the variation in power factor is mostly attributable to the variability inherent in the composition of the ROM ore. It is worth remarking that the designed capacity of the primary crusher is 38 000 tons per day, curiously, the historical data reveals that feed rates exceeded 50 000 tons per day. Graph B shows reduced variance in power factor when increased levels of pre-processed ROM was fed through later stages of crushing. Graph C shows how the moisture content in ROM ore influenced crusher power factor. For some reason, the power factor seemed to vary less with increased moisture in the ROM ore, albeit it that the relevant data that was available in this regard was relatively. Interestingly, the historical data plotted in graph D revealed wide variability in the crusher power factor with increasing ROM Fe, even though the power factor was mostly clustered between 0.7 and 0.8. A striking observation from the four graphs is that the crusher power factor varied widely between 0.2 and 0.88.

6.0 Concluding Remarks

Despite the irregularities associated with data obtained from the available historical records, however, the graphs briefly discussed in the preceding section provide empirical evidence of how the power factor of the crushing machines varied with ROM feed rate, particle size distribution, moisture and iron content. The results more or less validated the hypotheses, albeit that the wide variance in the crusher power factor highlights the main difficulty associated with optimizing the energy consumption of crushing and screening of run-of-mine iron ore. This difficulty is consistent with the view expressed earlier (re: Yamashita et al. 2021) that these exogenous signals can be measured but cannot necessarily be manipulated by plant operators. During the study, it was fascinating that these ROM variabilities were not really being manipulated in a manner to improve the power factor of the crushers. The apparent lack of motivation also highlights the pragmatic challenge of continuous optimization of energy consumption concomitant with reduction in CO_2 footprint.

The empirical study briefly described in this paper reinforces the following acclaimed issues. Firstly, the paramountcy of establishing appropriate methods (e.g., synchronization of data sampling rates) for the collection and collation of both endogenous and exogenous signals respectively representing the internal and external dynamics associated with comminution unit operations. Secondly, the importance of pertinent knowledge and capability to analyze, fuse and synthesize the large amounts quantitative data and qualitative information to, at least, facilitate continuous optimization of energy consumption during ore comminution operations. Acknowledging that there is so much intrigue regarding the preponderance of the need to adopt and implement fourth industrial revolution (4IR) technologies, however, the third issue is how to rapidly transform comminution activities to adapt towards achieving the sustainability imperatives of concurrently reducing pollution and CO_2 footprint during minerals processing operations.

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