Predicting Granulating Behaviour of Iron Ores Based on Size Distribution and Composition

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Increased demand and diminishing high grade resources have resulted in a large diversity of iron ore sources used in the modern steel mill. Using research on the effect of ore type and size on granulation for single ore blends containing coke, flux and returns, this paper presents a study to model the optimum granulating moisture and related green bed permeability of an iron ore from the size distribution and composition of the ore when added in a simplified sinter blend.

The models developed from the granulation test work are applied to a broad range of iron ore types and blends. The effect of particle size on granulation is also quantified across a range of iron ore types. It was found that the optimum moisture could be described accurately by knowing the ore’s SiO₂, LOI, and Al₂O₃ (≤1 mm) content, as well as the 0.15 mm and percentage of Intermediate (0.1 to 1 mm) size fractions. It was also found that for most iron ores, an increase in particle size close to the 0.1 mm size range has the greatest effect of reducing permeability and increasing granulating moisture.

KEY WORDS: granulation; sintering; iron ore and particle size; moisture; permeability; model.

1. Introduction

Before iron ore can be sintered, it must be granulated to improve sinter bed permeability. Research into granulation has been progressing over several decades. Initial work by Newitt et al. and Capes et al. on damp sand advanced the fundamental understanding of the granulating process. This work was followed more specifically by research into iron ore granulation to identify key factors by Furui et al., Yoshinaga et al. and Roller et al. These factors include the feed component characteristics and operating conditions of the granulation process. Subsequent iron ore granulation research has been directed towards these areas, or has combined these fields with attempts to predict granulation outcomes using mathematical models. This has been assisted by significant improvements in the fundamental knowledge of granulation summarized by Litster.

The iron ore industry has been working on blend design and ore design for some time. One component that will assist in blend design is understanding how an individual ore will affect the blend’s granulating ability and therefore productivity during sintering.

Work by Matsumura et al. provides a model to predict the optimal granulating moisture of an ore or ore blend from the saturation moisture (water retention value) and particle voidage (open void volume) of the blend components. Work by Yoshinaga et al. provides a model to predict granulation permeability by knowing a number of raw material characteristics and operating factors. These include densities of the components and blend, particle sizes and amount of absorbed water.

To avoid the need for additional test work on an ore, a simple model is required that should be based on readily available information about an ore, i.e., the ore’s composition and size distribution, to allow easy estimation of the ore’s optimum granulating moisture and related green bed permeability. Additionally and most importantly, this model should be based on a simulated sinter blend, since returns, flux and fuel will all affect granulating behaviour.

A study was conducted into the effects of ore type and size distribution on granulation for seven ores covering a broad range of ore types. The aim of this paper is to present granulation models that are based on an ore’s composition and size distribution and simulate the addition of an ore to a sinter blend containing coke, flux and returns.

2. Materials and Methods

2.1. Overview

Seven commercial grade iron ore samples were studied in the experimental work. The composition of the ores studied is provided in Table 1. The iron ore samples were prepared and granulated with fuel, flux and return fines components to assess the optimum moisture requirement for the highest green bed permeability. Data was also collected to size and characterise each ore sample and to determine the size distribution and structure of the granulated mixture following rapid freezing with liquid nitrogen. The procedure is summarised in Fig. 1.

2.2. Raw Materials

The ores studied were examined and classified petro-
graphically (see Fig. 2). The ores, in order of increasing goethite content, are described briefly below, focussing on characteristics relevant to granulation properties. These include (a) particle shape: equigranular particles roll and accumulate coatings, whereas elongated particles tend to slide; (b) hardness/mineralogy: hard, dense particles tend to fracture, forming coarse fragments, whereas soft, porous particles tend to abrade, producing large amounts of fine material; (c) surface characteristics: microporous particles tend to have a rough surface texture, which helps adhering particles to “key-in” to the surface and (d) gangue type: quartz tends to occur as discrete, relatively coarse particles and does not assist granulation, whereas clays break down to fine particles, which, with fine goethite, assist in binding adhering fines to the surface of granules.

Dense Hematite (DH): This ore is made up of relatively equigranular dense and porous hematite, with minor (ochreous) goethite and hematitic shale. Interlayered BIF-derived quartz-hematite is present and impurities are mainly in the form of discrete quartz grains.

Coarse Microplaty Hematite (CMH): Particles tend to be elongated and largely consist of aligned, coarse microplates of hematite, which have smooth surfaces and lack internal microporosity. Microporosity of the particles is generally low to moderate. Fine microplaty hematite/goethite particles are also present. Impurities are mainly from BIF (silica as quartz).

Fine Microplaty Hematite (FMH): Consists largely of microporous particles made up of fine hematite microplates, with some layered microplaty/granular hematite zones and minor dense hematite. Dense hematite-goethite and vitreous goethite are present in minor amounts. Impurities are quartz and minor clay minerals.

Hematite/Marra Mamba (H/MM): Variable ore texture; moderately porous overall, ranging from dense hematite–goethite to friable hematite–goethite and goethitic components, with local dense vitreous goethite and hydrohematite. Gangue is mainly as yellow (goethitic) shale and kaolinitic clay, with minor quartz.

High alumina Pisolite Ore (HAP): Consists of macroporous aggregates of kaolinitic goethite-cemented pisoliths. Pisolith cores are of hydrohematite, vitreous and ochreous goethite and shale. Fossil (goethitised) wood fragments are common. The soft ochreous goethite tends to be enclosed within vitreous goethite and size reduction is mainly by fracturing of aggregates, resulting in a relative lack of ultrafine material in the ore.

Low Alumina Pisolite Ore (LAP): Similar to HAP ore, but with gangue mainly as quartz, occurring as pore linings and fillings. Vitreous-ochreous goethite pelloids are also characteristic; these tend to be microporous rather than macroporous, and somewhat “earthy” in nature.

The other components of the blends were sinter returns, limestone, silica sand and coke breeze. The silica sand and limestone were from a commercially available source, while the sinter return fines were created from several sinter plugs, crushed to ~90% ~5 mm. The coke breeze was from a sinter plant.

2.3. Feed Component Preparation

Bulk samples of each ore, the coke breeze and limestone were initially homogenised. The samples were processed by screening to create subsamples with the following modified size distributions; low fines (removal of ~0.07 mm), low nucleus (removal of +2.8 mm) and varying amounts of intermediate particles (adjust sizing to allow ~20%, ~40%,
Representative samples were used for characterisation, dry sizing and determining the moisture content of each feed component. For each component, the saturation moisture (M_s) was also determined; this was defined as the maximum percentage of moisture that the sample could hold without dripping during a simple filtration test.

2.4. Sinter Blend Targets and Granulation

From the ore chemistry and initial moisture content, the blend of 15 kg (total dry weight) was created based on 5.0% SiO_2 in the sinter product, 4.0% coke breeze (total dry mass basis), 1.8 basicity (the CaO : SiO_2 ratio in the sinter product) and 30% returns (ore basis). Moisture was varied from dry to wet conditions to assess the granulability of the ores.

Granulation was conducted in a rotating drum (internal diameter: 500 mm, length: 250 mm) and consisted of 4 min of cataracting motion at 35 rpm and 5 min of cascading motion at 15 rpm. Samples were immediately taken to assess the actual moisture and permeability of the granules and the granule size distribution.

2.5. Permeability Measurement

The green bed permeability of the wet mix was measured as the pressure drop across a 250 mm deep by 150 mm diameter bed. The test was conducted at an air flow rate of 400 L·min^{-1}. A second test, to assess the strength of the green bed, was performed after each permeability measurement was taken, where a 4.5 kg load was applied evenly to the top of the granule bed for 10 s and the new pressure drop measured at the same air flow rate. The amount of bed deformation was determined by subtracting the unloaded pressure drop from the loaded pressure drop. At least one repeat of each test was performed.

The pressure drop values were converted into Japanese Permeability Units (JPU). JPU values calculated using Eq. (1) are independent of the granule bed dimensions and airflow (Shimomura et al. in Yoshinaga).

\[ JPU = \frac{Q}{A} \left( \frac{H}{DP} \right)^{0.6} \]

2.6. Frozen Granule Size Distribution and Petrology

To measure the granule size distribution and obtain petrology samples, the wet granules were frozen with liquid nitrogen and duplicate samples of the frozen granules were then screened using five sieves of 8, 4, 2, 1 and 0.5 mm. The size distribution for each test and the rate of growth of the granules with feed moisture was then determined.

3. Raw Materials Analysis

All raw materials were blended and homogenised prior to samples being prepared for chemical analysis (Table 1) and size distribution determination (Figs. 3 and 4).

3.1. Chemistry and Saturation Moisture

The seven ores chosen covered a broad range of ore types, as shown in Table 1. The predominately hematitic ores were represented by DH, CMH and FMH. These ores are all low in LOI_{371°C} (<1 mass%), but range in grade from 65 to 68% Fe. The hematite-goethite ores were represented by H/MM and MM. These ores have low to medium LOI_{371°C} and slightly lower grades (61 to 64% Fe). The pisolitic ores were represented by HAP and LAP. The LOI_{371°C} of these ores is quite high at ~8% and the grade has dropped to between 57% and 59% Fe. These two ores have greatly differing alumina contents (1.4% and 2.7%).

Table 1 also shows the difference between the ore head chemistry and ~0.063 mm (adhering fines) chemistry, providing an indication of the distribution of gangue components with size. Fine “sticky” kaolinite is likely to enhance granule binding, whereas smooth, discrete quartz grains are unlikely to have any beneficial effect on granulation. Of the ores studied, FMH, H/MM and MM all have kaolinite as the major gangue component in the adhering fines and this is expected to correlate with the good granulation performance of these ores. In the case of HAP, the coarse overall sizing of the ore and lack of liberated ultrafine kaolinite over-rides the presence of kaolinite as gangue.

3.2. Size Distribution

As well as a range of ore types, the size distribution of the ores studied varied over a d_{50} range from 0.8 to 2.2 mm (Fig. 3). As seen in Fig. 4, the size distribution variation results in a significant difference in the quantity of adhering, intermediate and nucleus particles. Of the ores studied, DH had a high nucleus component with low adhering fines. HAP and LAP had low adhering fines, while CMH, FMH and MM had high adhering fines.
4. Discussion and Analysis of Data
4.1. Comparison of Ore Types

Each ore blend consisting of ore, coke, flux and returns, was granulated at a range of moisture contents and optimum conditions were chosen based on the highest green bed permeability.

Granulation performance varied dramatically with ore type. Figure 5 shows low magnification reflected optical photomicrographs of typical granule structures for the seven ore types, at optimum moisture level. The DH ore formed granules with irregular, but overall relatively thin coatings and a high proportion of dense nuclei, reflecting the dense nature of the ore and relative lack of ultrafine material.

CMH ore nuclei had partial coatings of fines, which included individual hematite microplates (note that the dense, elongated nucleus particle at the top of the image in Fig. 5 has almost no adhering fines layer). Conversely, a number of aggregate particles, consisting of several small “nuclei”, cemented by intermediates/ultrafines, were seen. A number of quartz particles (Qz) can be seen within the coating layers.

The FMH ore showed rather incomplete coating layers in spite of the more favourable sizing, again reflecting the relatively poor granulating properties of clean, microplaty hematite ores. Note that the large nucleus at bottom centre of the micrograph appears dark due to the dominant presence of ultrafine (submicron) hematite microplates.

The H/MM ore nuclei were surrounded by thick, continuous coating layers of goethite, hematite, flux and fuel particles and large aggregate particles were also present.

The coating layers around the mostly porous MM gran-
ules were thick, resulting in well-rounded granules, and an abundance of ultrafine goethitic/kaolinitic material was evident, enhancing binding of the outer layer and providing impact absorption via plastic deformability.

The HAP macroporous, pisolithic ore nuclei showed somewhat incomplete fines layers, consisting of relatively coarse particles which appeared to be only tenuously bound (e.g. the particle at far right of the image).

The LAP ore had even less uniform fines layers than HAP ore, varying from locally thick, to completely absent, apparently depending largely on the local surface texture of the nucleus particles (smooth, flat vitreous goethite surfaces seem particularly unfavourable for adhesion). Only a low proportion of ultrafine adhering fines particles was seen.

**Figure 6** shows the relationship between moisture content and green bed permeability (JPU) for each ore. The curves all show the same trend of improved permeability as moisture is increased due to granule coating development. Optimal permeability is reached before high moisture results in flooding and deformation/collapse of the granule coating with a subsequent loss of permeability.

Based on the premise that optimal granulating moisture for a blend and the related green bed permeability (JPU) can be predicted from basic ore information, i.e., composition and particle size distribution, the effect of each of these characteristics was considered individually on the granulating parameters. It was found that no single component from the ore’s composition or size could fully explain the granulating behaviour of the ore. This is a complex multi component system requiring a number of component interactions to be included to explain granulating behaviour.

The objective was to determine through granulation trials the optimal moisture for granulation of an ore in a simulated sinter bed. The optimal moisture was determined by the lowest moisture at which the moisture-permeability curve achieved a minimum when DP based or a maximum when JPU based. The permeability at this moisture content was also noted. The measurement and control of feed moisture was excellent with a standard deviation of 0.05% H$_2$O. This was significantly better than that of permeability, which had a standard deviation between 0.5 and 2.0 JPU.

The statistical analysis package Minitab Version 14 was used to conduct the data analysis and determine the regression correlations using stepwise linear regression to determine the parameters with strongest correlations, followed by sensitivity analysis using multilinear regression. Data analysis was conducted on the basis that the final model should only include data readily available for an ore, i.e., composition and size distribution, to allow the model to be readily used as a tool to predict an ore’s granulation behaviour without requiring additional test work. Therefore, while moisture saturation was found to be a strong parameter for both prediction of optimal moisture and the related permeability, the final model did not include this component, as an additional test would need to be conducted to determine the saturation moisture of the ore.

The key granulating parameters from the experimental work on optimal moisture, permeability (as JPU) and the intermediate particle loading are shown in **Fig. 7**. For each ore type, it was apparent that there was a good relationship between variation in the intermediate particle loading and the resultant granulating moisture content and permeability. Where a significant change was made to the ore by removing particles below 0.075 mm (binding particles) or removing nucleus particles above 2.8 mm (points underlined in **Fig. 7**), this had a significant effect on the ore’s granulating performance, shifting the relationship away from the expected curve for varying intermediate particle loading. Commercial iron ores fines with no +2.8 mm or −0.075 mm fraction are rare, so it was decided not to include these results in the modelling work.

Once the models were developed, each model was tested against the granulating data from sinter test work covering a

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**Fig. 6.** Comparisons of ore permeability as a function of moisture content.

**Fig. 7.** Granulating test data showing optimal moisture, permeability and intermediate size loading. Samples where the +2.8 mm fraction was removed have been underlined.
broad range of ores and ore blends. Both the granulating model and model testing data sets are shown in Fig. 8.

5. Results and Discussion

5.1. Prediction of Optimal Moisture

The following Eq. (2) was found to predict the optimal granulating moisture for an ore,

\[
W_{opt} (\text{wt%}) = 2.28 + 0.427 \text{LOI (wt%)} + 0.810 \text{Al}_2\text{O}_3 (\text{wt%}) + 0.339 \text{SiO}_2 (\text{wt%}) + 0.104 \left[ \frac{d}{d_{0.15}} \right] + 0.0359 \%I. \quad R^2_{adj} = 96.3\% \quad \cdots \cdots \cdots (2)
\]

To test the accuracy of the predicted optimal moisture, the model was applied to granulation results covering a wide range of ores and blends, the spread of which can be seen in Fig. 8. As seen in Fig. 9, the model was able to predict the optimal moisture for both the single ores (R^2 of 0.863) and ore blends (R^2 of 0.807).

At this point, it is important to discuss the limitations of the optimum moisture model by reviewing the target sintering conditions it was based on. The model was developed with a simulated single ore blend with a target of 5.0% SiO2 in the sinter product, 4.0% coke breeze (total dry mass basis), 1.8 basicity (the CaO : SiO2 ratio in the sinter product) and 30% returns (ore basis). To test the model, a test data set was used covering a wider range of conditions. The ore modelling testing data has a SiO2 content ranging from 4.8 to 6.4%, coke breeze rate of 3.4 to 4.7%, basicity of 1.7 to 1.9, returns rate of 30 to 35% (ore basis) and no lime addition. The ore blend modelling testing data has a SiO2 content ranging from 4.4 to 5.7%, coke breeze rate of 3.5 to 4.7%, basicity of 1.8 to 2.0, returns rate of 27 to 36% (ore basis) and up to 0.9% lime addition. As demonstrated in Fig. 9, the model appears to work well when applied within the target limits 4.4 to 6.4% SiO2, 3.4 to 4.7% coke breeze rate, 1.7 to 2.0 basicity, 27 to 36% returns rate (ore basis), and lime does not seem to effect the predicted results when below 0.9%. It is uncertain how well this model will predict the optimum moisture outside the above specified range.

Each component within the model was significant in determining the optimum moisture. Each of these factors is examined individually in the discussion below.

There are three components related to the composition of the ore. The total LOI of an ore is a good indication of its goethite content and provides an indication of internal porosity, since high-LOI ochreous goethite tends also to be highly microporous. The internal porosity will determine moisture absorption and therefore affect the optimum granulating moisture. As indicated by the positive sign, the model indicates that, as the total LOI of the ore increases, the optimal moisture is also expected to increase, but by 43% of the increase in LOI. The Al2O3 content of the ore is generally associated with either kaolinite or gibbsite, with the clay or kaolinite being more significant in the finer fractions. The −1 mm fraction of ores will contain the fine clay component, which will absorb moisture readily. As again indicated by the positive sign in the model, as the Al2O3 in the −1 mm fraction of the ore increases, the optimal moisture will increase by 80% of the increase in −1 mm Al2O3. Flux in the form of fine sand was added to achieve the silica target for the sinter blends. Less flux is required when the ore contains silica in the form of quartz or kaolinite. The adsorption of water by fine flux increases the optimum moisture content. Consequently, the model indicates that an increase in the silica content of the ore will reduce the optimum moisture content (by 34% of the increase in silica).

The other two factors in the model are related to the size distribution of the ore. Both indicate that an increase in the

Fig. 8. Spread of key values for the granulation ores used to develop the models and both ores and ore blends data used to test the models.

Fig. 9. Comparison of predicted granulation optimal moisture with actual granulation optimal moisture for both single ores and ore blends.
intermediate particle size loading (mass fraction between 0.1 and 1 mm) and the $-0.15$ mm fraction will increase the optimum moisture content by $\sim 4\%$ and $\sim 10\%$ respectively of the increase in each size fraction.

To gain a better understanding of the effect of the size distribution of an ore on the granulating optimum moisture content, the experimental data was plotted in terms of the change in optimum moisture content against the increase in mass in each size fraction. The resultant curves for each ore type are shown in Fig. 10. The result is very interesting and provides an insight into the effect of ore size distribution on optimum granulating moisture content. As can be seen, the intermediate particles (those between 0.1 mm and 1 mm) cause an increase in the optimum granulating moisture content while the binding particles (those below 0.06 mm) and the nucleus particles (those above 1 mm) cause the granulating moisture content to decrease. The most interesting trend is the very strong negative effect that particles in the 0.1 mm size fraction have on the optimum moisture content, causing the largest increase. At this point, it is useful to recall that the optimum granulating moisture content is the lowest moisture content at which the highest permeability is achieved. Figure 10 indicates that an increase in particles around 0.1 mm results in more moisture being required to achieve a stable granule coating.

Of interest is also the difference in behaviour of the different ore types, especially in the 0.1 mm size range. The largest increase in moisture is observed with the pisolitic ores, while the more hematitic ores show a lesser effect in this size range. Insufficient data was available on the DH, due to the small number of particles in this size fraction. The effect of the intermediate particles and the large effect of the 0.1 mm size fraction explain the predicted behaviour of the two size factors in the model. There is a great deal of information in Fig. 10 on both the behaviour of different ores and the effect of particle size.

In summary, a model to predict the optimal granulating moisture content for an ore or ore blend has been developed that operates over a reasonable range of sintering target conditions. This model is based on the $\text{SiO}_2$, $\text{Al}_2\text{O}_3$($\leq 1$ mm) and LOIT contents of the ores or ore blends, as well as the intermediate particle loading ($0.1$, $1$ mm) and the proportion of ore in the $-0.15$ mm size fraction.

5.2. Prediction of Optimum Permeability

The following Eq. (3) was found to predict the permeability for an ore at optimal moisture,

$$P_{\max} \text{(JPU)} = 28.6 + 1.22 \text{LOIT (wt\%)} + 3.85 \text{Al}_2\text{O}_3(\leq 1$ mm)(wt\%) - 2.97 \text{SiO}_2(\text{wt\%}) + 0.593[d_{0.64-1}] - 1.83[d_{0.06-0.15}] + 0.831[d_{0.06-0.063}] + 0.282[\%I], \quad R^2_{\text{adj}} = 87.8\% \quad \text{..........................(3)}$$

Again, the permeability model was tested for granulating results covering a broad range of single ores and ore blends (Fig. 8). The results of the comparison between the predicted and actual optimum permeability are shown in Fig. 11. Predicting optimal permeability was a lot more difficult than predicting optimal moisture due to the greater scatter in the data. As seen in Fig. 11, the model could only explain $51\%$ of the behaviour of the single ores and was significantly worse at predicting ore blend permeability. One clear problem was the significant effect lime addition (used as a binder to improve granulation) has on permeability (see Fig. 11), which had not been factored into the model. Clearly more work is required to achieve a better prediction of optimal permeability. The approach taken in this study of developing a model based on ore composition and size distribution alone is not sufficient to predict permeability.

To gain a better insight into the effect of particle size on green bed permeability across the range of ores studied, the change in permeability was plotted against increase in particle size fraction as shown in Fig. 12. It is important to note before studying the curves in Fig. 12, that permeability in this case is measured as $DP$ (Pa), i.e., the resistance gen-
erated across the green bed to a standard air flow rate of 400 lpm. This is the inverse of a JPU measurement and therefore will have a similar shape to the optimum moisture curve. The resultant curves, while similar in shape to that for optimum moisture content, shows an increased effect of the coarser ore size fraction on permeability than that seen for optimum moisture content. Clearly increasing particles in the +6.3 mm size fraction will result in a significant improvement in permeability, resulting in a large decrease in pressure drop across the green bed (DP). Again binding particles, while few in number, have a large effect on improving permeability (reducing DP).

Particles in the 0.1 mm size range have the greatest detrimental effect on permeability (causing the largest increase in DP). Of the ores investigated, the CMH ore with its smooth surfaces caused the largest reduction in permeability between 0.1 and 1 mm.

Based on the intermediate particle behaviour of the various ore types in Fig. 12, it is possible to create an ore type factor to apply to the intermediate size fraction in the permeability model. A simple method would be to consider the behaviour of the CMH ore as the standard and relate the behaviour of each ore in the intermediate size fraction (0.1 to 1 mm) to that of the CMH ore. Creating a new model base on the granulating test data, which included an ore type factor did improve and simplify the permeability model, but a problem was then encountered in determining what ore type factor to apply to the wider range of ores in the main data set. As shown in Fig. 13, there is no clear trend in the ore type factor, requiring each ore to be tested to determine this factor before its permeability can be predicted using the model. It is clear more work needs to be done before a simple model for predicting green bed permeability can be developed.

In summary, while a model to predict optimal permeability was presented, it could only explain 51% of the variance of single ores and was unsuccessful in explaining the behaviour of ore blends, more work is required to account for the effect of lime addition in the model and to account for the ores’ surface properties.

6. Conclusion

In conclusion, the aim of this study was to develop a simple model that used the ore composition and size distribution to determine the optimal granulating moisture content and permeability. A model for predicting optimal moisture content was successfully developed and demonstrated. It was found that predicting optimal permeability was more difficult, and while explaining ~51% of the variance of a single ore, the model could not be applied to ore blends and requires both lime addition and surface behaviour to be taken into account. The effect of particle size on optimal moisture content and permeability across a range of ores was shown. It was also found that for most iron ores, an increase in the number of particles close to the 0.1 mm size range had the greatest effect of reducing permeability and increasing granulating moisture content.

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Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>DH</td>
<td>Dense hematite</td>
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<tr>
<td>CMH</td>
<td>Coarse microplaty hematite</td>
</tr>
<tr>
<td>FMH</td>
<td>Fine microplaty hematite</td>
</tr>
<tr>
<td>H/MM</td>
<td>Hematite/Marra Mamba</td>
</tr>
<tr>
<td>MM</td>
<td>Marra Mamba</td>
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<tr>
<td>HAP</td>
<td>High alumina pisolite</td>
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<tr>
<td>LAP</td>
<td>Low alumina pisolite</td>
</tr>
<tr>
<td>Q</td>
<td>Airflow (m³/min)</td>
</tr>
<tr>
<td>A</td>
<td>Cross-sectional area of the bed</td>
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<tr>
<td>Popt</td>
<td>Permeability in JPU at optimal granulating moisture (m²)</td>
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<tr>
<td>Wopt</td>
<td>Predicted optimal granulating moisture in weight percentage on a total mix basis</td>
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<td>LOIγ</td>
<td>Weight percentage of LOI in the ore</td>
</tr>
<tr>
<td>Al₂O₃(−1.0mm)</td>
<td>Weight percentage of −1.0 mm alumina in the ore</td>
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<tr>
<td>SiO₂</td>
<td>Weight percentage of silica in the ore</td>
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<td>%I</td>
<td>Fraction of ore between 0.1 and 1 mm</td>
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<td>R² adj</td>
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REFERENCES