

# Optimization of Particle Size and Specific Surface Area of Pellet Feed in Dry Ball Mill using Central Composite Design

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## Abstract

**Objective:** The dimensional properties of iron ore pellet feed including specific surface area and particle size distribution in the ball mill was studied using response surface area method. **Methods/Statistical analysis:** The effect of the operational parameters of dry ball mill including ball charge (20-40%), grinding time (30-50 min) and balling distribution (Small, Mixed and Large) on dimensional properties of pellet feed was meticulously examined and optimized using response surface methodology based on Central Composite Design (CCD). Responses were 80% passing size (D80) and Blaine (BL). A total of 30 grinding experiments were designed and carried out in the CCD method. Regression models and response surfaces were obtained for each response. **Findings:** The results predicted by these models showed good agreement with experimental values. In the studied range it was deduced that D80 is decreased and BL increased when grinding time and ball charge increased. Also, the production of fine particles improved using balling distribution of level B (mix balls), instead of one ball size distribution. 3D graphs were applied to visually evaluate each parameter effect on responses. The optimum conditions of ball mill operational parameters to reach the best pellet feed for each blast furnace burden and direct reduction iron (DRI) pellet feed were revealed using CCD optimization. The predicted values BL and D80 were found to be in a reasonable agreement with the experimental values, with R2 as correlation factor being 0.91 and 0.92 for BL and D80, respectively. **Improvements:** The optimum condition for having a suitable blast furnace burden was: Ball distribution level B, Ball charge= 21.8-22.4 %, Grinding time= 40.1-42.9 min. Also, the optimal condition for DRI pellet feed preparation was: Ball distribution level B, Ball charge= 21.8-22.1 %, Grinding time= 42.1-44.6 min.

**Keywords:** Ball Mill, Central Composite Design, Particle Size, Pelletizing, Specific Surface Area

## 1. Introduction

Iron ore pellet feed need a distribution size of minus 106  $\mu\text{m}$  from fine grinding. As separation circuits reduce the fines fraction to less than the required specific surface area (e.g. Blaine  $\text{cm}^2/\text{g}$ ), it is necessary to regrind concentrates to facilitate generation of a suitable pellet feed for further treatment in the balling and firing steps. Based on industrial data, to prepare suitable iron-making feed the specific surface area of the pellet feed should be approximately 1800 and 2000  $\text{cm}^2/\text{gr}$  for blast furnace burden and Direct Reduction Iron (DRI) pellet feed, respectively. The formation of high quality pellets with a

good drop number, compression strength and porosity via a suitable mix of additives depends on the proportion of fines defined by both size distribution and specific surface area<sup>1,2</sup>. In pelletizing plants in Iran, pellets are mainly produced by magnetite concentrate, which produces a lower strength of green pellet occurs due to its coarser size and poor pellet-ability feed<sup>3,4</sup>.

In mineral processing plants two main methods are used for the concentrate grinding; High Pressure Grinding Rolls (HPGR) and wet or dry ball mill. The dry ball mill method has been of great interest in the Iranian pelletizing plants so far because of a higher content of undersize particles and also difficulties in the production

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of concentrate filter cake compared with wet conditions. In the dry ball mill method, the produced wet concentrate of belt filter is charged to the ball mill. In the first step of ball mill, the concentrate is dried down to 3% using hot flow air (without steel balls) and afterward is ground in the ball mill. Dry ball milling is one of the most economic and efficient techniques for the preparation of fine and ultra-fine dispersions of particulate materials<sup>5,6</sup>. The crushing events are predominantly generated by particle-balls-contacts. This contact promotes inter-granular breakage and more likely a spherical particles shape<sup>7</sup>.

The application of flexible statistical software, such as Response Surface Methodology (RSM), reduces the time required on the relevant analyses by resorting to the formulation of a robust design matrix, which is engineered to yield precisely configured experimental trials within the ordered ranges of variables. Furthermore, the empirical models developed using the RSM technique explicitly takes into account the linear, quadratic, polynomial and interaction effects of various process parameters, thereby resulting in suitable and practical predictions for near optimal process factor levels in the assigned region of operability<sup>8-11</sup>.

Despite pellet feed grinding being a prerequisite for most pelletizing plants, to the best of our knowledge, a grinding optimization study on pellet feed using dry ball mill has not been reported so far. The aim of the present research is to investigate effective operational parameters of dry ball mill on the dimensional properties of pellet feed. For modeling, some applied operational parameters i.e. the ball charge, grinding time and balling distribution were considered as the variables and  $D_{80}$  and BL as the relevant responses, as both  $D_{80}$  and BL were proved to be successful for the determination of feed fineness<sup>12</sup>. In addition, the optimum conditions for reaching the most suitable pellet feed for each blast furnace burden and DRI-pellet were studied.

## 2. Experimental

### 2.1 Sample Analysis

The iron ore concentrate was obtained from Gol-e-gohar line 5 plant located in Kerman province, Iran. The  $D_{80}$  and BL of concentrate were 133  $\mu\text{m}$  and 937  $\text{cm}^2/\text{gr}$ , respectively. The chemical and screening analysis of concentrate is presented in the Table 1.

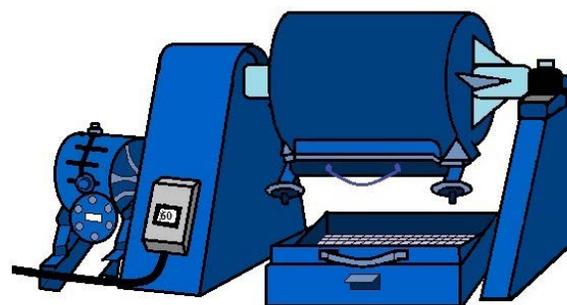
**Table 1.** The chemical and size distribution analyses of the iron ore concentrate

Chemical Analysis	(%)	Size Distribution	(%)
Fe <sub>total</sub>	69.85	-150 $\mu\text{m}$	85.0
FeO	26.75	-106 $\mu\text{m}$	72.0
S	0.13	-90 $\mu\text{m}$	64.8
P	0.05	-75 $\mu\text{m}$	56.4
MgO	0.41	-53 $\mu\text{m}$	41.1
CaO	0.18	-45 $\mu\text{m}$	36.7
Al <sub>2</sub> O <sub>3</sub>	0.25	-38 $\mu\text{m}$	30.2
SiO <sub>2</sub>	1.19	-25 $\mu\text{m}$	22.3
L.O.I.	2.58		

## 2.2 Experimental Procedure

### 2.2.1 Dry Ball Mill

The experiments were performed in a laboratory ball mill having the diameter of 312 mm, length of 284 mm, working volume of 21.2 liter equipped with eight steel liners with dimension of 12×24×270 mm (H×W×L). The rotational speed of ball mill was constant equal to 70 rpm. Firstly, the ball mill was partly charged with an identified level of ball distribution and ball charge, and then a specific amount of iron ore concentrate (4000 g  $\pm$  5 g) with moisture less than 3% was charged to the ball mill. After the set grinding time, the ball mill was stopped and all of iron ore concentrate was discharged. It is very important to discharge the ball mill completely and clean the balls using an air blower before running the next test. Figure 1 shows the schematic of the laboratory ball mill.



**Figure 1.** Schematic of laboratory ball mill.

### 2.2.2 Blaine Air Permeability

After ball mill grinding each product was riffled technically and a 100 g sample was taken for a Blaine test. The test was performed under the ASTM C 204 standard method. The sample was first alcohol washed to de-agglomerate ore particles and then dried in an oven. The dried sample was passed through a suitable screen to completely separate all particles. A specific amount of concentrate, based on concentrate true density measured by Pycnometer, was weighed and placed in the cell. The specific surface area of concentrate is measured using the passing time of air through the concentrate bed, by the equation (1):

$$BL = k \times t^{0.5} / \rho \tag{1}$$

where, BL is specific surface area, K is coefficient constant derived from standard sample, t is passing time through the bed and ρ is true density of concentrate.

The schematic view of Blaine meter apparatus is shown in Figure 2.

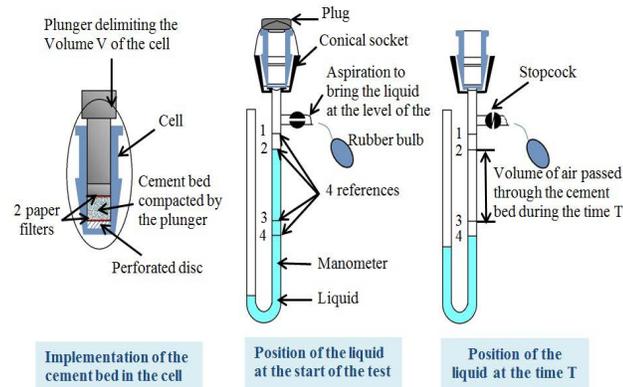


Figure 2. Blaine meter apparatus for the measurement of specific surface area.

### 2.2.3 Screening Analysis

The wet screening analysis was performed in order to calculate  $D_{80}$ . 100 g riffled sample was placed on the upper screen (125 μm) and water was passed with the flow rate of 1 lit/min and collected in a plastic container (water plus particles less than 25μm). The screening time was 30 min and the screen shook with a constant frequency. At the end of test, from coarser to finer size, the sample of each screen was dried and then weighed with accuracy of 0.01 gr.

### 2.3 Experiment Design

The response surface method (RSM) is one of the statistical tools of experimental design, which optimizes the operational factors and moreover constructs a descriptive mathematical model for the process<sup>13,14</sup>. A Central Composite rotatable experimental Design (CCD) was chosen in the present study to model and optimize the ball mill grinding process and to analyze the effect of each parameter, their interaction and second order terms. The number of tests required for CCD included the standard  $2^k$  factorial with its origin at the  $\pm 1$  level,  $2k$  points fixed axially at a distance  $\pm\alpha$  from the center to generate the quadratic terms and replicate tests at the center (or 0 levels); where k is the number of variables. An appropriate mathematical model for prediction of the grinding behavior of iron ore particles can be extracted using CCD design.

The codes are calculated as functions of the range of interest of each factor as shown in Table 2.

Table 2. Relation between coded and actual values of parameters

Code	Actual value of parameters
-α (axial)	$X_{min}$
-1 (factorial)	$[(X_{max} + X_{min})/2] - [(X_{max} - X_{min})/2\alpha]$
0 (center)	$(X_{max} + X_{min})/2$
+1 (factorial)	$[(X_{max} + X_{min})/2] + [(X_{max} - X_{min})/2\alpha]$
+α (axial)	$X_{max}$

The effect of three important parameters in the grinding process such as balling charge and grinding time (quantitative parameters) and balling distribution (qualitative parameter) has been assessed. The range of variables and their levels for the quantitative parameters and qualitative parameter are presented in the Tables 3 and 4, respectively.

Table 3. Quantitative parameters with their levels

Parameters	Notation	-α	-1	0	+1	+α
Ball charge (%)	$X_1$	20	25	30	35	40
Grinding time (min)	$X_2$	30	35	40	45	50

Table 4. Qualitative parameter with its level

Parameter	Notation	Level A	Level B	Level C
Ball distribution	$X_3$	100%	50% 15mm balls+ 23mm balls	100% 23mm balls

The total number of required tests can be determined by the equation (2):

$$N = M \times (2^k + 2k + N_0) \tag{2}$$

where, N is test runs, M is levels of qualitative parameter, K is quantitative parameters and  $N_0$  is center point tests.

### 3. Results and Discussion

Table 5 lists the ranges and levels of the applied parameters (30 runs), the designed CCD matrix, and the experimental and predicted responses. The variable ranges were indicated based upon some preliminary experiments.

### 3.1 Process Modeling

The stepwise fit modeling was used by ‘Design Expert’ software (version 7.0.0). To calculate the predicted responses, the quadratic polynomial response was suggested as equation (3):

$$R = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=2}^k \beta_{ij} x_i x_j + \epsilon \quad i \neq j \tag{3}$$

Where R,  $x_i$  and  $x_j$ , i and j denote the response variable, actual independent variables, and index numbers for patterns, respectively.  $i < j$  must be observed for the interaction terms ( $x_i x_j$ ). k is the number of input variables.  $\beta_0$ ,  $\beta_i$ ,  $\beta_{ii}$  and  $\beta_{ij}$  are intercept term, linear, quadratic and interaction effects, respectively.  $\epsilon$  symbolizes the random error accounting for the differences between experimental and predicted results.

**Table 5.** The designed experiments by CCD methodology and corresponding responses

Run	$X_1$ (%)	$X_2$ (min)	$X_3$	BL (cm <sup>2</sup> /gr)		$D_{80}$ (μm)	
				Experimental	Predicted	Experimental	Predicted
1	30	40	Level A	2115	2045	35	36
2	25	35	Level C	1589	1686	47	45
3	40	40	Level B	2488	2567	30	28
4	30	40	Level B	2309	2166	32	36
5	35	35	Level C	1737	1872.2	43	42
6	20	40	Level C	1753	1647	42	43
7	20	40	Level A	1681	1675	44	45
8	30	40	Level A	1989	2045	37	36
9	25	45	Level A	1846	1950	39	38
10	30	50	Level C	2428	2390	31	31
11	40	40	Level A	2003	2055	37	37
12	40	40	Level C	2168	2043	34	38
13	35	35	Level A	2050	2024	36	36
14	35	45	Level C	2265	2274	33	34
15	20	40	Level B	1337	1405	56	53
16	30	30	Level B	1913	1938	39	40
17	25	45	Level B	2085	1920	38	40
18	25	35	Level B	1655	1729	45	45
19	30	30	Level A	1900	1904	39	39
20	30	40	Level B	2233	2166	33	34
21	30	40	Level C	1947	2025	38	37
22	30	40	Level C	1929	2025	39	37
23	30	50	Level A	2208	2136	34	34
24	30	50	Level B	2235	2344	34	33
25	35	45	Level A	2164	2153	34	35
26	25	35	Level A	1878	1847	40	41
27	35	35	Level B	2288	2298	32	32
28	35	45	Level B	2613	2513	29	30
29	30	30	Level C	1758	1610	44	45
30	25	45	Level C	2062	2064	36	37

### 3.1.1 BL Modeling

For each ball distribution (A, B and C), the final regression model equation fitted to the experimental response of BL was represented in terms of the actual parameters as equations (4-6):

$$BL = -708.6 + 117 \times X_1 + 24.1 \times X_2 + 0.25 \times X_1 \times X_2 - 1.8X_1^2 - 0.25X_2^2 \text{ For level A} \tag{4}$$

$$BL = -2108.3 + 156 \times X_1 + 32.8 \times X_2 + 0.25 \times X_1 \times X_2 - 1.8X_1^2 - 0.25X_2^2 \text{ For level B} \tag{5}$$

$$BL = -1848.3 + 117 \times X_1 + 51.5 \times X_2 + 0.25 \times X_1 \times X_2 - 1.8X_1^2 - 0.25X_2^2 \text{ For level C} \tag{6}$$

The suggested model was checked using the Analysis Of Variance (ANOVA) that has been summarized in Table 6.

**Table 6.** ANOVA results for the response quadratic polynomial model of BL

Effect	P- value (Prob.>F)	F value	Source
Significant	<0.0001	13.32	Model
Significant	<0.0001	65.42	X <sub>1</sub> (Ball charge)
Significant	<0.0001	32.58	X <sub>2</sub> (Grinding time)
Significant	0.0322	4.18	X <sub>3</sub> (Ball distribution)
Significant	0.0009	10.53	X <sub>1</sub> X <sub>3</sub>
Significant	0.0337	4.12	X <sub>2</sub> X <sub>3</sub>
Significant	0.0158	7.1	X <sub>1</sub> <sup>2</sup>
-	0.1248	4.38	Lack of fit

The results indicate that the model is statistically significant and can be used as a predictor of the experimental data. The significance of the model terms

was evaluated based upon the P-value (Prob>F) at 95% confidence level. It indicates the model terms are significant if P-value for each term is less than 0.05. The significant terms were X<sub>1</sub>, X<sub>2</sub>, X<sub>1</sub>X<sub>3</sub>, X<sub>1</sub><sup>2</sup>, X<sub>3</sub> and X<sub>2</sub>.X<sub>3</sub>, respectively.

The coefficient of determination (R<sup>2</sup>) measures the proportion of total variability explained by the model. It is suggested that for a good-fitting model R<sup>2</sup> should be close to 1 and at least 0.80. The adequate precision measures the signal-to-noise ratio, and values greater than four are desirable. The coefficient of variation (C.V. =5.92%) is the standard deviation expressed as a percentage of the mean and should be less than 10%<sup>15-17</sup>. Based on Table 7, these model statistics values also corroborated the propriety of the developed response surface model<sup>18</sup>.

### 3.1.2 D<sub>80</sub> Modeling

For each ball distribution (A, B and C), the second-order polynomial model determined for the D<sub>80</sub> value and independent variables (X<sub>1</sub> and X<sub>2</sub>) were shown below as equations (7-9):

$$D_{80} = 131.1 - 3.96 \times X_1 - 1.31 \times X_2 + 0.017 \times X_1 \times X_2 - 0.048X_1^2 - 0.008X_2^2 \text{ For level A} \tag{7}$$

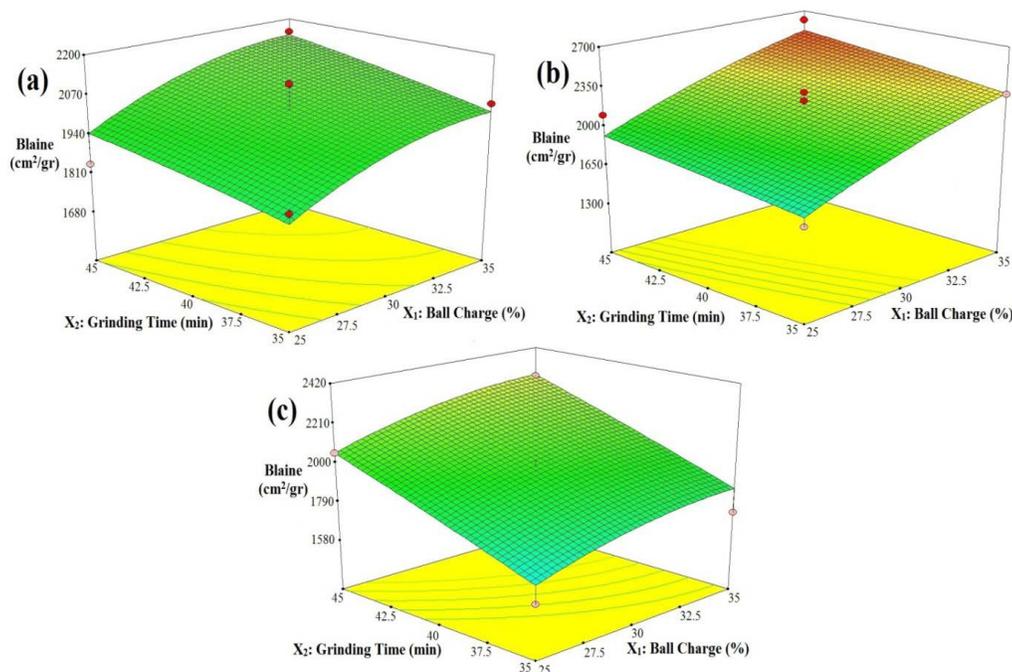
$$D_{80} = 161.4 - 4.78 \times X_1 - 1.47 \times X_2 + 0.017 \times X_1 \times X_2 - 0.048X_1^2 - 0.008X_2^2 \text{ For level B} \tag{8}$$

$$D_{80} = 152.8 - 3.97 \times X_1 - 1.82 \times X_2 + 0.017 \times X_1 \times X_2 - 0.048X_1^2 - 0.008X_2^2 \text{ For level C} \tag{9}$$

The analysis of variance (ANOVA) is an important criterion which presents the significance of model and terms<sup>18,19</sup>. The results are shown in Table 8.

**Table 7.** Model statistics for the response quadratic polynomial model of BL

Adeq. Precision	Pred. R-Squared	Adj. R-Squared	R-Squared	C.V.%	Mean	Std. Dev
15.36	0.63	0.83	0.89	5.92	2017.4	119.47



**Figure 3.** Response surface plots showing the variation in BL as a function grinding time and ball charge for (a) ball distribution A (b) ball distribution B (c) ball distribution C.

**Table 8.** ANOVA results for the response quadratic polynomial model of  $D_{80}$

Effect	P- value (Prob.>F)	F value	Source
Significant	<0.0001	10.94	Model
Significant	<0.0001	55.89	$X_1$ (Ball charge)
Significant	0.0001	24.14	$X_2$ (Grinding time)
-	0.3309	1.18	$X_3$ (Ball distribution)
-	0.5804	0.32	$X_1X_2$
Significant	0.0014	9.71	$X_1X_3$
-	0.0746	3.01	$X_2X_3$
Significant	0.0043	10.69	$X_1^2$
-	0.6202	0.25	$X_2^2$
-	0.0709	6.74	Lack of fit

The F-value of 10.94 and Prob>F of <0.0001 justified the model significance with a 0.01% chance that variation may occur because of noise (effect of some uncontrollable variables on normal working conditions causing some induced variations). Prob>F values less than 0.05 indicate

the significant terms of model, in this part as can be seen from the Table 8,  $X_1$ ,  $X_2$ ,  $X_1X_3$  and  $X_1^2$  were the significant terms.

Based on Table 9, both  $R^2$  and Adj. $R^2$  were relatively high and in reasonable agreement. A very low coefficient of variation (C.V. =6.98%) is an indication of a high degree of precision and reliability among experimental values. Adequate precision measures the signal to noise ratio, a ratio greater than 4 is desirable, in this case ratio of 14.45 for  $D_{80}$  proves a very suitable signal which insinuate that this model can be used to steer the design space.

### 3.2 Effect of Model Parameters on BL

The behavior of the model approximated response surface with BL as the response, when iron ore concentrate subjected to the grinding by ball-mill, was graphically represented by means of the 3-dimensional response surface plots shown in Figure 3. The ball distribution is qualitative and so it is necessary to depict a plot for each ball distribution (3 plots for each response). As the

**Table 9.** Model statistics for the response quadratic polynomial model of  $D_{80}$

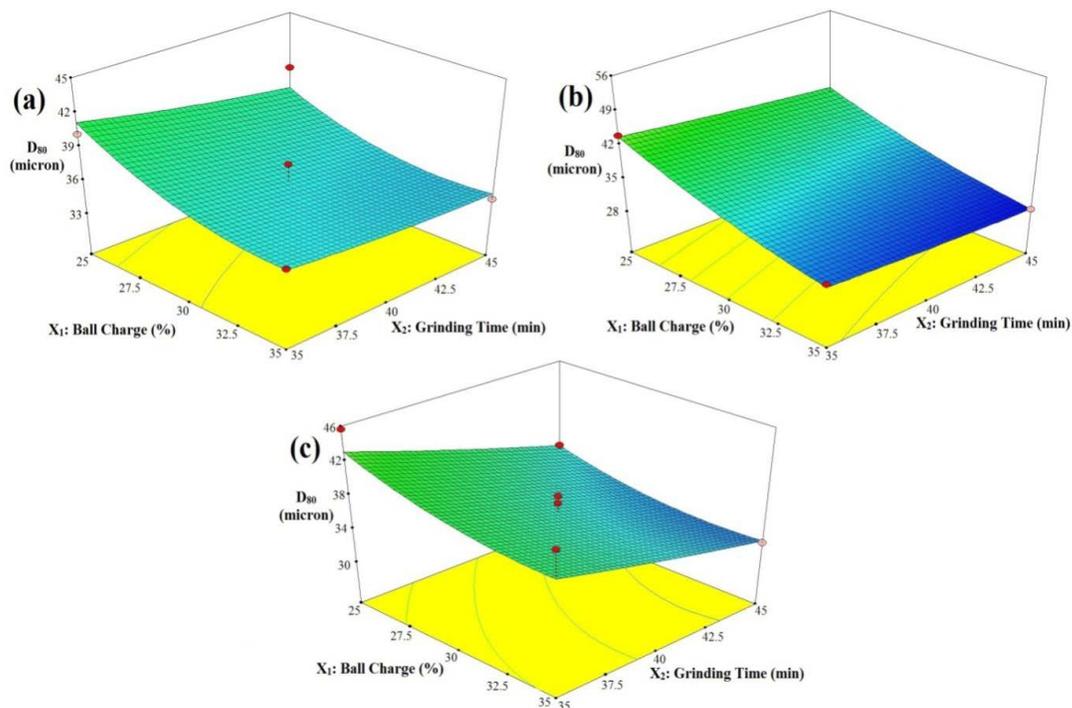
Adeq. Precision	Pred. R-Squared	Adj. R-Squared	R-Squared	C.V.%	Mean	Std. Dev.
14.45	0.61	0.80	0.87	6.98	37.45	2.62

color gets red, the response increases. Both Eq. (4-6) and the response surface plot (Figure 3) suggest that the BL increases with increase of both grinding time and ball charge at the chosen range. Also ball distribution has interactive effects with each of grinding time and ball charge. The contour gradient in grinding time coordinate direction is less than that in ball charge coordinate direction, which shows that ball charge, is more important than grinding time to achieve higher BL. At low ball charge (25–30%, green zones) the increase in grinding time didn't have a significant effect on the BL. However, at high ball charge (30–35%), increasing the grinding time resulted in BL increase. The higher BL was observed at high ball charge and long grinding time. It was deduced that at the same conditions, balling distribution of level B (50% 15mm balls + 50% 23mm balls) provides higher BL. This occurs due to the higher filling degree of ball-mill volume using mix balls which causes higher point contacts between balls and particles. Higher contacts resulted in more impacts and accordingly a higher specific surface<sup>20,21</sup>.

### 3.3 Effect of Model Parameters on $D_{80}$

Based on the model, effect of the operating factors on the

$D_{80}$  value was again investigated by three dimensional surface graphs. In 3D graphs of Figure 4, the effect of two parameters, ball charge and grinding time, is surveyed whereas the other one (Ball distribution) is maintained constant. Blue color indicates the decrease of  $D_{80}$  value and surroundings of optimum conditions. It demonstrates that the  $D_{80}$  is decreased with increasing of the grinding time. Also, this decreasing trend of  $D_{80}$  versus grinding time is observed at both high and low amount of ball charge, which implies there is no considerable interactions between these operating factors. Also, add in the ball charge will promote the  $D_{80}$  down to a certain amount, while no significant effect is accompanied with further addition (>35%). Marks on the surface of three-dimensional plots show areas of individual models, and it is clear that critical values of independent variables (optimum conditions) lie within appropriate models. The interaction of ball charge and ball distribution should also be considered. Based on the response surface plot shown in Figure 4, it can be seen that at mix ball distribution (B: 50% 15mm balls + 50% 23mm balls)  $D_{80}$  improves. However, at first by increase of large balls numbers (23 mm)  $D_{80}$  decreases highly and afterward increases slowly. In fact, there is an optimum ball distribution resulted in better  $D_{80}$  value<sup>22</sup>.



**Figure 4.** Response surface plots showing the variation in  $D_{80}$  as a function grinding time and ball charge for (a) ball distribution A (b) ball distribution B (c) ball distribution C.

### 3.4 Optimization of Dimensional Properties of Pellet Feed

Fine iron ore concentrate is used as feed for pelletizing plant. The produced pellet is fed to the iron-making plant as an important raw material. Two important iron-making methods, namely blast furnace (BF) and direct reduction iron (DRI), use pellets as iron resource. One of the most important properties of pellet feed is cold compression strength (CCS). CCS should be higher than 250 and 300 Kg/p for BF and DRI pellet feed, respectively. A direct relevance between CCS and BL exists; higher BL resulted in higher CCS<sup>23,24</sup>. To achieve the CCS requirement, it has been proven that BL should be more than 1800 and 2000 cm<sup>2</sup>/gr for BF and DRI pellet feed, respectively<sup>1,2,3</sup>.

Response Surface Methodology (RSM) has been extensively applied in the optimization of various processes<sup>8-12</sup>. As outlined 2 outputs namely BL and D<sub>80</sub> were used as the properties of pellet feed. Here, optimization of the process means finding of operating factors value to reach a desired point of the BL and D<sub>80</sub>, based on the proposed reduced RSM model. Practically, the goals of variables were set "in the range" (For ball distribution variable were set on level A or B or C) and the goal of response range was set at BL of 1800 and 2000cm<sup>2</sup>/gr for BF and DRI pellet feed respectively. The result of grinding optimization based on desirable range is shown in Tables 10 and 11.

The optimum conditions to achieve suitable blast furnace burden with BL of 1800 cm<sup>2</sup>/gr is presented in Table 10. By using all the above described settings and boundaries, the software predicted following conditions for each ball distribution:

Ball distribution level A: X<sub>1</sub>=23.6-24.3 %, X<sub>2</sub>=41.0-42.4 min, BL =1800 cm<sup>2</sup>/gr, D<sub>80</sub> =42.2-42.8 μm.

Ball distribution level B: X<sub>1</sub>=21.8-22.4 %, X<sub>2</sub>=40.1-42.9 min, BL =1800 cm<sup>2</sup>/gr, D<sub>80</sub> =40.8-41.2 μm.

Ball distribution level C: X<sub>1</sub>=23.3-24.9 %, X<sub>2</sub>=39.7-42.3 min, BL =1800 cm<sup>2</sup>/gr, D<sub>80</sub> =41.4-41.8 μm.

The optimal values of variables to attain suitable DRI pellet feed with BL of 2000 cm<sup>2</sup>/gr is shown in Table 11. The predicted optimal conditions for each ball distribution are as follows:

Ball distribution level A: X<sub>1</sub>=23.6-24.4 %, X<sub>2</sub>=40.9-41.8 min, BL =2000 cm<sup>2</sup>/gr, D<sub>80</sub> =38.3-38.4 μm.

Ball distribution level B: X<sub>1</sub>=21.8-22.1 %, X<sub>2</sub>=42.1-44.6 min, BL =2000 cm<sup>2</sup>/gr, D<sub>80</sub> =36.6-36.8 μm.

Ball distribution level C: X<sub>1</sub>=23.0-24.9 %, X<sub>2</sub>=41.1-42.4 min, BL =2000 cm<sup>2</sup>/gr, D<sub>80</sub> =37.1-37.2 μm.

Both Tables 10 and 11 proved that achieving to specific BL using ball distribution level B needs less amount of ball charge and grinding time compared with level A or C. This will happen due to the sufficient grinding energy, higher impact points between balls and particles and increase in the collision frequency between the balls and particles;

**Table 10.** Results of process optimization and optimum conditions of concentrate grinding for blast furnace burden

No.	X <sub>1</sub> (%)	X <sub>2</sub> (min)	X <sub>3</sub>	BL (cm <sup>2</sup> /gr)		D <sub>80</sub> (μm)		Desirability
				Experimental	Predicted	Experimental	Predicted	
1	24.1	42.1	A	1762	1800	43	42	1.000
2	24.2	41.8	A	1760	1800	43	42	1.000
3	23.6	42.4	A	1845	1800	42	43	1.000
4	24.3	41.0	A	1789	1800	42	43	1.000
5	22.0	42.3	B	1778	1800	42	41	1.000
6	22.4	40.1	B	1848	1800	41	41	1.000
7	22.4	40.3	B	1837	1800	40	41	1.000
8	21.8	42.9	B	1840	1800	42	41	1.000
9	23.8	42.3	C	1773	1800	43	42	1.000
10	24.6	43.3	C	1765	1800	42	41	1.000
11	24.9	42.1	C	1834	1800	43	41	1.000
12	23.3	39.7	C	1815	1800	41	42	1.000

in fact, use of larger balls is useful for mineral grinding under dry condition due to the impact or compressive forces of the grinding ball<sup>25,26</sup>.

To check accuracy of the optimizations, further confirmatory experiments were conducted using the supposed values of the parameters. The relationships between the experimental data and predicted values attained from the CCD model, was illustrated in Figure 5 (a, b) with square correlation coefficient,  $R^2$  equal to 0.91 and 0.92 for BL and  $D_{80}$  respectively which are in good agreement with the predicted efficiencies by the model. This indicates that the developed model is robust and insensitive to external noise or tolerances by changing the factors.

### 4. Conclusion

In this research, modeling of dry ball mill grinding process, using RSM and CCD design was investigated. Ball

charge, grinding time and balling distribution were the process control variables while BL and  $D_{80}$  of the product were considered as the response. ANOVA described good statistical coefficients for BL and  $D_{80}$  modeling, thus ensuring an acceptable adjustment of the quadratic polynomial response model with the experimental data. The most significant factors which affected both BL and  $D_{80}$  were ball charge and grinding time. It was deduced that a higher ball charge and grinding time along with the balling distribution of level B resulted in better fine particles production; because of higher impact points between balls and particles. The optimum condition for having a suitable blast furnace burden was introduced as: Ball distribution level B, Ball charge=21.8-22.4%, Grinding time=40.1-42.9min. Also, the optimal condition for DRI pellet feed preparation was estimated as: Ball distribution level B, Ball charge=21.8-22.1 %, Grinding time=42.1-44.6min. Promising results also suggest that RSM can be tested and developed for grinding modeling of other ores.

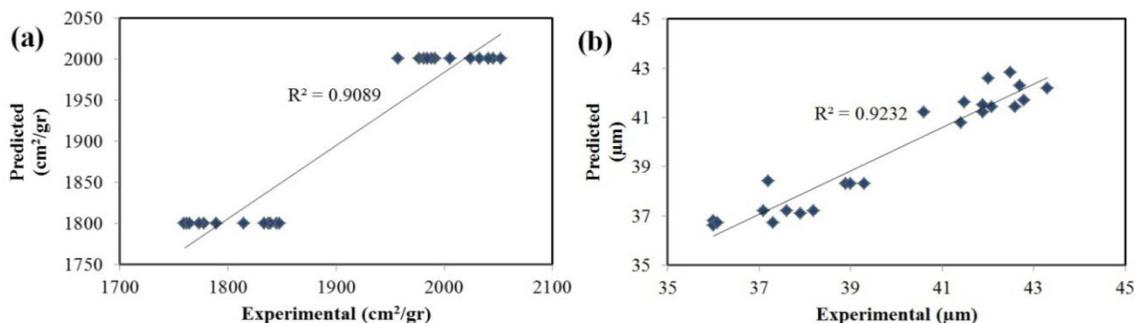


Figure 5. Comparison between the Predicted values and experimental results (a) BL (b)  $D_{80}$ .

Table 11. Results of process optimization and optimal values of concentrate grinding for DRI pellet feed

No.	$X_1$ (%)	$X_2$ (min)	$X_3$	BL ( $cm^2/gr$ )		$D_{80}$ ( $\mu m$ )		Desirability
				Experimental	Predicted	Experimental	Predicted	
1	24.4	40.9	A	1992	2000	39	38	1.000
2	24.2	41.5	A	2033	2000	37	38	1.000
3	23.6	41.7	A	2045	2000	39	38	1.000
4	24.2	41.8	A	1977	2000	39	38	1.000
5	21.8	43.2	B	1988	2000	36	37	1.000
6	22.0	42.7	B	1981	2000	37	37	1.000
7	21.8	44.6	B	2005	2000	36	37	1.000
8	22.1	42.1	B	1985	2000	36	37	1.000
9	23.0	42.2	C	2025	2000	38	37	1.000
10	24.1	41.1	C	2041	2000	38	37	1.000
11	24.9	42.3	C	2052	2000	38	37	1.000
12	23.8	42.4	C	1958	2000	37	37	1.000

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## 6. References

1. Van der Meer FP. Pellet feed grinding by HPGR. *Minerals Engineering*. 2015; 73:21.
2. Qiu G, Zhu D, Pan J, Wang C, Guo Y, Jiang T, Hu C, Clout J, Shu F. Improving the oxidizing kinetics of pelletization of magnetite concentrate by high press roll grinding. *ISIJ International*. 2004; 44(1):69.
3. Jian-Jun F, Guan-Zhou Q, Tao J, Yu-Feng G, Hai-Zheng H, Yong-Bin Y. Mechanism of high pressure roll grinding on compression strength of oxidized hematite pellets. *Journal of Central South University of Technology*. 2012; 19:2611.
4. Van der Meer FP. High pressure grinding moving ahead in copper, iron, and Gold processing. *The Southern African Institute of Mining and Metallurgy 6<sup>th</sup> Southern African Base Metals Conference*; 2011.
5. Abu-zied BM, Schwiager W, Asiri AM. Effect of ball milling on the structural and textural features of MCM-41 mesoporous material. *Microporous and Mesoporous Materials*. 2015;218:153.
6. Monov V, Sokolov B, Stoenchev S. Grinding in ball mills: Modeling and process control. *Cybernetics and Information Technologies*. 2012; 12:51.
7. Fandrich R, Gu Y, Burrows D, Moeller K. Modern SEM-based mineral liberation analysis. *International Journal of Mineral Processing*. 2007; 84:310.
8. Abazarpour A, Halali M, Maarefvand M, Khatibnezhad H. Application of response surface methodology and central composite rotatable design for modeling and optimization of sulfuric leaching of rutile containing slag and ilmenite. *Russian Journal of Non-Ferrous Metals*. 2013, 54:388.
9. Raei-Niaki A, Abazarpour A, Halali M, Maarefvand M, Ebrahimi G. Application of response surface methodology and central composite rotatable design for modeling and optimization of sulfuric and nitric leaching of spent catalyst. *Russian Journal of Non-Ferrous Metals*. 2015; 56:155.
10. Abazarpour A, Halali M, Khatibnezhad H. Optimization of acid leaching of rutile containing slag using factorial based response surface modeling. *Indian Journal of Science and Technology*. 2016 Jan; 9(4):1-8.
11. Devi BDK, Vijayalakshmi P, Shilpa V, Prasad T, Kumar BV. Response surface methodology for the optimization of Kojic acid production by *Aspergillus flavus* using *Muntingia calabura* fruits as a carbon source. *Indian Journal of Science and Technology*. 2015 Mar; 8(6):556-61.
12. Meyer K. *Pelletizing of iron ore*. Springer Berlin Heidelberg; 1980.
13. Dutta S, Bhattacharyya A, Ganguly A, Gupta S, Basu S. Application of response surface methodology for preparation of low-cost adsorbent from citrus fruit peel and for removal of methylene blue. *Desalination*. 2011; 257:26.
14. Ghodsiyeh D, Golshan A, Hosseiniyehzad N, Hashemzadeh M, Ghodsiyeh S. Optimizing finishing process in Welding of Titanium Alloy (Ti6Al4V) by zinc coated brass wire based on response surface methodology. *Indian Journal of Science and Technology*. 2012 Oct; 5(10):1-13.
15. Im JK, Cho IH, Kim SK, Zoh KD. Optimization of carbamazepine removal in O<sub>3</sub>/UV/H<sub>2</sub>O<sub>2</sub> system using a response surface methodology with central composite design. *Desalination*. 2012; 285:306.
16. Onsekizoglu P, Bahceci KS, Acar J. The use of factorial design for modeling membrane distillation. *Journal of Membrane Science*. 2010; 349:225.
17. Chakraborty S, Dasgupta J, Farooq U, Sikder J, Drioli E, Curcio S. Experimental analysis, modeling and optimization of chromium (VI) removal from aqueous solutions by polymer-enhanced ultra-filtration. *Journal of Membrane Science*. 2014; 456:139.
18. Fang X, Wang J, Wang Y, Li X, Zhou H, Zhu L. Optimization of ultrasonic-assisted extraction of wedelolactone and antioxidant polyphenols from *Eclipta prostrata* L using response surface methodology. *Separation and Purification Technology*. 2014; 138:55.
19. Ghitescu RE, Volf I, Carausu C, Bühlmann AM, Gilca I A, Popa VI. Optimization of ultrasound-assisted extraction of polyphenols from sprucewood bark. *Ultrasonics Sonochemistry*. 2015; 22:535.
20. Sabah E, Özdemir O, Koltka S. Effect of ball mill grinding parameters of hydrated lime fine grinding on consumed energy. *Advanced Powder Technology*. 2013; 24:647.
21. Garcia F, Le Bolay N, Frances C. Changes of surface and volume properties of calcite during a batch wet grinding process. *Chemical Engineering Journal*. 2002; 85:177.
22. Ebadnejad A, Karimi GR, Dehghani H. Application of response surface methodology for modeling of ball mills in copper sulphide ore grinding. *Powder Technology*. 2013; 245:292.
23. Umadevi T, Kumar MGS, Kumar S, Gururaj Prasad CS, Ranjan M. Influence of raw material particle size on quality of pellets, Ironmak. *Steelmak*. 2008;35:327.
24. Zhu D, Pan J, Qiu G, Clout J, Wang C, Guo Y, Hu C. Mechano-chemical activation of magnetite concentrate for improving its pellet-ability by high pressure roll grinding. *ISIJ International*. 2004; 44:310.
25. Zhang J, Bai Y, Dong H, Wu Q, Ye X. Influence of ball size distribution on grinding effect in horizontal planetary ball mill. *Advanced Powder Technology*. 2014; 25:983.
26. Kotake N, Kuboki M, Kiya S, Kanda Y. Influence of dry and wet grinding conditions on fineness and shape of particle size distribution of product in a ball mill. *Advanced Powder Technology*. 2011; 22:86.