ANALYSIS OF TWO-LAYER SINTERING PROCESS FOR DIFFERENT BED HEIGHTS BY GENETIC ALGORITHM

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Abstract: Iron ore sintering having two-layers, with normal coke rate in the top layer and lower coke rate in the bottom layer can significantly reduce the overall coke rate and improve the sinter quality by producing optimum thermal profile and melting fraction throughout the bed height. For optimum design of the two-layer sintering process we have to evaluate the coke rate and thickness of the two layers. The two main objectives of the sintering process are sinter quality and reduction of coke rate, which is investigated here by multiobjective optimization to evaluate the Pareto optimum points, which gives the competitive optimum points with respect to the two conflicting objectives. The total height of the sinter bed can vary significantly in industrial practice, and thermal efficiency or coke rate improves with higher bed height, which however requires higher suction pressure. This study gives a good insight into the effect of sinter bed height on quality and coke rate.

Keywords: Two-layer Sintering, Iron Ore, Coke rate, Sinter Quality for Melting, Multiobjective Optimization, Pareto Set, Genetic Algorithm.

1. INTRODUCTION

Iron ore sintering is a complex high temperature gas-solid reaction process for bulk production of blast furnace raw material. The quality of sinter is very important for smooth operation and high productivity of blast furnace since it improves the permeability and reducibility of the burden material. The process have been analyzed by the detailed CFD based model considering all the important phenomena like flow through porous bed, heat and mass transfer, gas-solid reaction, melting and solidification (Nath, *et al.*, 1997). Sinter quality is mainly dependent on the melting fraction, which again depends on the temperature profile during sintering. Very low melting will cause insufficient sinter strength resulting in high return fines. Excessive melting will result in homogeneous glassy structure, which has very low reducibility. Therefore optimum melting is necessary for good quality of sinter. A heterogeneous texture consisting primarily of unreacted porous

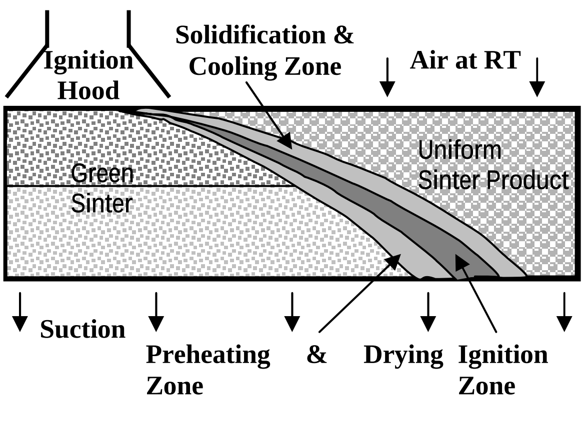

Fig. 1. Two-layer sintering process.

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hematite ore bonded by acicular calcium ferrites is reported to be optimum (Formoso, *et al.*, 2003; Dawson, 1993). Two-layer sintering with normal coke rate in the top layer and lower coke rate in the bottom layer can significantly reduce the overall coke rate and improve the sinter quality by producing optimum thermal profile and melting fraction throughout the bed height, as schematically shown in Fig. 1. Optimization techniques like genetic algorithm is applied to evaluate the optimum conditions for quality, productivity and thermal efficiency of two-layer sintering process

2. MATHEMATICAL MODEL FOR SINTERING

The mathematical model for the sintering process is capable of calculating the solid and gas temperatures and compositions at any position of the sinter bed during its operation (Nath *et al.*, 1997). To achieve this a dynamic model in two-dimensional Cartesian coordinate system has been developed, neglecting the variation in the transverse direction. The gas velocity through the bed is estimated from the Ergun's pressure drop equation by an iterative method. All the other process variables are evaluated by solving the transient forms of the appropriate transport equations. The set of equations used for modeling the process is therefore consisted of:

1. Gas velocity profile by Ergun's pressure drop equation.
2. Solid phase thermal energy balance.
3. Gaseous phase thermal energy balance.
4. Solid phase mass or species balance.
5. Gaseous phase mass or species balance.

2.1 Ergun's Pressure Drop Equation

Gas velocity during sintering was estimated by an iterative method from Ergun's pressure drop equation for a given pressure drop. As sintering progresses through the drying and melting stages, porosity and grain size increase substantially changing the gas velocity in the packed bed, which was estimated on the basis of a previous work (Cummings, *et al.*, 1990) and incorporated in Ergun´s equation given as:

$$\frac{\Delta P}{L} = \frac{150\mu . V(1-\varepsilon)^2}{d_p^2 \varepsilon^3} + \frac{1.75 . \rho_g . V^2 (1-\varepsilon)}{d_p \ \varepsilon^3} \qquad (1)$$

2.2 Generalized equation

A generalized solver was used to solve the variables like temperature of gas (T_g), temperature of solid (T_s), and concentration of the gaseous species (G) like : O_2, CO, CO_2, H_2, H_2O, as shown below:

$$\frac{d\varphi}{dt} + \left(V_x \frac{d\varphi}{dx} + V_y \frac{d\varphi}{dy} \right) = \alpha \left(\frac{d^2\varphi}{dx^2} + \frac{d^2\varphi}{dy^2} \right) + S_c + S_p \varphi \qquad (2)$$

Where φ is any pertinent transport variable, and S_c, S_p are source terms. The source terms are different for each particular case ($\varphi = T_s, T_g, G$). At the inlet boundary, temperature and composition of solid and gas are known, and at outlet zero gradient condition is used, details are given elsewhere (Nath *et al.*, 1997).

Table 1. Sintering reaction and phase transformation

	Reaction name	Formula
1	Reduction of Iron oxides	$Fe_2O_3 \rightarrow Fe_2O_3 \rightarrow FeO \rightarrow Fe$
2	Decomposition of Limestone	$CaCO_3=CaO+CO_2$
3	Coke combustion	$C+O_2=CO_2$; $2C+O_2=2CO$
4	Boudourd reaction	$C+CO_2=2CO$
5	Water gas reaction	$C+H_2O=CO+H_2$
6	Water gas shift reaction	$H_2O+CO=CO_2+H_2$
7	Formation of water vapor	$H_2+0.5O_2=H_2O$
8	Drying and condensation	$\langle H_2O \rangle=(H_2O)$
9	Melting and Solidification	[Solid Sinter]⇔ <Liquid Sinter>

2.3 Solid Phase Mass or Species balance

The solid phase can be evaluated from the kinetic models taken from literature. However, since the bed in the present case is not static but moving, we have to incorporate the convective terms in the rate expression to account for the solid velocity as given below:

$$\frac{dX}{dt} + V_s \frac{dX}{dx} = \Sigma \frac{R_i}{\rho_{s,i}} \qquad (3)$$

2.4 Sintering Reactions

The important reactions and phase transformations during the sintering process, considered for developing the model are listed in **table 1**. Details of the reaction kinetic models and parameters are given in the previous publications (Nath, *et al.*, 2004), and so not reproduced here.

3. PROCESS OPTIMIZATION BY GENETIC ALGORITHM

In the field of traditional optimization, the less robust derivative based optimization techniques are often used for handling single and multiobjective optimization problems (Deb, 2001). Unfortunately, an excellent initial guess of the optimal solutions is required for this kind of traditional optimization technique. This means one must almost know the optimal solution even before solving the problem. Sometimes engineering judgements are used to provide intelligent initial guesses but that need a prerequisite of the user being extremely intelligent with the solution techniques along with their domain knowledge which is very rare most of the times. This kind of demands made these techniques rather unpopular from the point of view of user-friendlyness. Recently, genetic algorithm (GA), and its adaptations for more useful but complex multiobjective optimization problems, have become very popular. Unlike conventional methods, these methods work with a bunch of initial guesses (not to be provided by a user), called population and generally have the capability of finding the global optimum in presence of several local optima. Simultaneously this robust algorithm is superior to traditional optimization algorithms in many aspects (Deb, 2001; Goldberg, 1989).

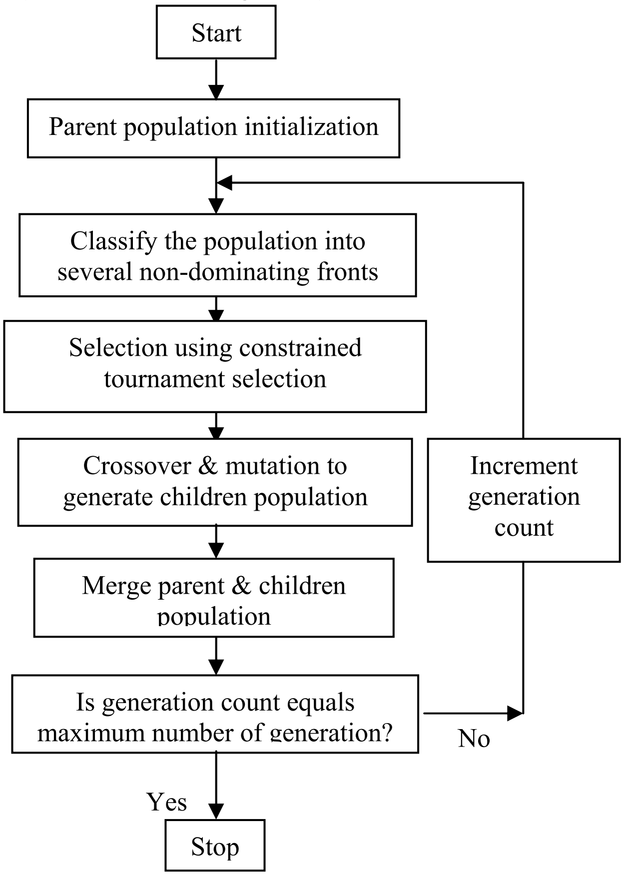

Fig 2: Flowchart of working principle of NSGA II

In case of multiobjective optimization, instead of a unique optimal solution, a set of equally good (nondominating) optimal solutions is obtained (Pareto sets). One popular way of solving multiobjective optimization problems is to solve a single objective optimization problem, which is a weighted-average of the several objectives. Unfortunately, the solution obtained by this process depends largely on the values assigned to the weighting factors used. This approach doesn't provide a dense spread of the Pareto points. Another popular way of solving a multiobjective optimization problem is to covert one or more of the objectives into constraints and solve a single objective optimization problem. In this case, solving the same problem many times by changing the constraint boundaries each time generates the whole Pareto set. The problem with this approach is also with getting a dense spread in the Pareto set as most of the time, changing constraint boundary leads to same final solution in the Pareto set. One has to run the optimization code minimum those many times as there are distinct number of solutions in the Pareto set. Among several methods available to solve multiobjective optimization problems, nondominated sorting genetic algorithm II (NSGA II) (Deb, *et al.* 2002), is used here to obtain the Pareto set which is free from all problems stated above. The set of operations carried out from one generation to the next, and the working principle of NSGA-II is schematically shown in fig. 2. NSGA based techniques have been used to solve a wide variety of multiobjective optimization problems in materials, metallurgical and chemical engineering in recent years like, sintering (Nath, et al., 2004; Nath, et al., 2003), continuous casting (Chakraborti, et al., 2001), ore beneficiation (Mitra, et al., 2004), industrial nylon-6 semibatch reactor (Mitra, et al., 1998) etc.

4. PROBLEM FORMULATION

The two objectives taken into consideration for this work are related to sinter quality and coke consumption where the former is maximized and the latter is minimized. For the present study it has been assumed that 30 % melting is optimum for the sinter quality for melting (SQM). The first objective (SQM) is, therefore, defined as having maximum value of 100 % when the melting is optimum (30 %) throughout the sinter bed and decreases linearly otherwise. The second objective (C_W) is the combined (weighted average) coke used in two layers of sintering. The decision variables are the coke used in upper (C_A) and lower (C_B) layers and the position of the boundary line (B) between the upper and lower layers. Decision variable bounds are used as constraints. The above multiobjective optimization problem can be stated as a standard nonlinear programming problem as follows:

$$\max_{C_A, C_B, B} \quad SQM$$

$$\min_{C_A, C_B, B} \quad C_W$$

subject to all model related continuity equations

Decision variable bounds:

$$C_A^L \le C_A \le C_A^U$$

$$C_B^L \le C_B \le C_B^U$$

$$B^L \le B \le B^U$$

Where superscript L and U denote the lower and upper bounds of the decision variables. The two objective functions used here are conflicting in nature and so it is likely that a Pareto set of nondominating optimal solutions can be obtained. The nondominated sorting genetic algorithm II

(NSGA II) is used to solve the problem defined above.
The mathematical model presented here is capable of calculating the solid and gas temperatures, melting fraction and compositions at any position of the sinter bed during its operation. The communication between the optimization code and the model occurs as follows. For each of the candidate solutions generated by optimization module, C_A, C_B and B values are supplied by the optimization code to the model. The model is solved for these decision variables along with other fixed design parameters for the given sintering bed and two final outputs (SQM and C_W) are returned back to the optimizer code. The whole process gets repeated several times to obtain the final solution.

5. RESULTS AND DISCUSSION

The objective of the present study is to optimize the two layer sintering process, to achieve high sinter

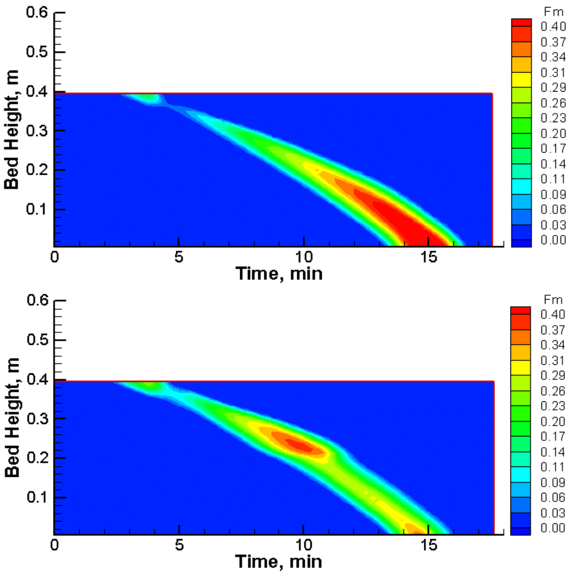

Fig. 3. Molten zone during sintering for (a) uniform coke rate, and (b) Two-layer sintering.

quality for melting (SQM) with minimum coke rate. Typical results for 40 cm bed height, with equal top and bottom layer thickness showed optimum results for coke rate of 7.4 % and 4.8 % in the top and bottom layer respectively, giving rise to an overall coke rate of 6.1 %. The results for mono-layer sintering with uniform coke rate of 6.1 % is compared with two-layer sintering, as shown in fig. 3. The results for mono-layer sintering showed melting is very low in the top critical zone just after the ignition hood, giving rise to high return fines; whereas melting is excessive or more than 40 % in the lower regions giving rise to glassy phase with very low reducibility. For two-layer sintering however, the melting is more or less uniform throughout the bed producing good sinter quality with high strength and reducibility. Optimization results of SQM value and coke rate for varying top layer thickness is shown in fig. 4. The result shows that both SQM and coke rate increases with decreasing top layer thickness. However, our

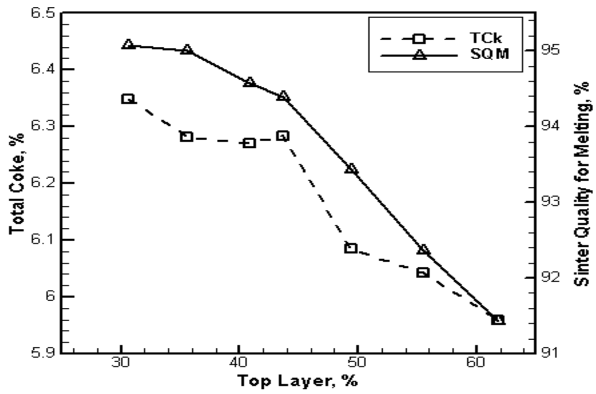

Fig. 4. Variation of coke rate and sinter quality for melting with top layer thickness.

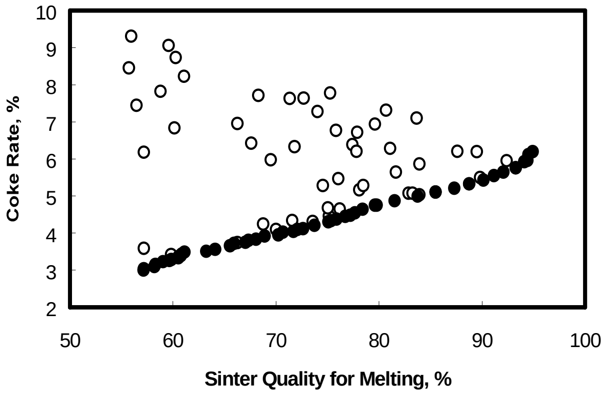

Fig. 5. Initial guess and Pareto optimum points shown by open and filled circles respectively.

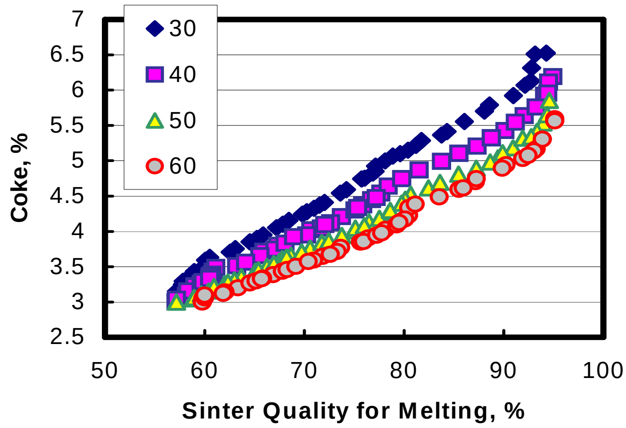

Fig. 6. Variation in Pareto optimum set points for sinter bed height of 30, 40, 50 and 60 cm.

objective is to increase the value of SQM and decrease the coke rate (conflicting sense), and so this becomes a multiobjective optimization problem.
The twin objective of optimizing the process by maximizing SQM and minimizing total coke rate by multiobjective optimization is achieved by simultaneously varying the manipulated or decision variables like coke rate in the top and bottom layers, and the thickness of top layer. Fig. 5 shows the randomly created initial population of the zeroeth

generation and the final converged Pareto optimum set points by empty and filled circles respectively. From the figure, we can observe that the Pareto set points define the boundary for lowest coke rate with maximum SQM values, whereas the initial guess points are scattered with many points having high coke rates and low SQM values. NSGA II was observed to take about three to four generations to converge to the final Pareto set. After convergence, it was found to maintain the same points in the Pareto fronts over any number of generations. The Pareto front shown in fig. 5 was a convex one.

Two most important issues of any multiobjective optimization study were (i) achieving the global Pareto front, (ii) achieving a dense spread in the final Pareto front. The first point was validated by two approaches: (i) generating different initial population (by changing the decision variable bounds) and checking whether the final Pareto fronts are same for all these different populations or not. (ii) Solving the multiobjective problems using a single-objective preference based optimization method (ε-constraint method). As both the cases stated above were true for the present study, the authors claim to achieve final solutions near or on the global Pareto front. As seen from fig. 5 (filled circles), spread obtained in the global Pareto front was quite dense. The final Pareto front was quite different from the randomly created population in the initial population (empty circles). This means with progress in generations, better nondominating fronts were evolved and finally the global Pareto front is achieved. The elitist approach of considering both parent and child population for selecting the better candidates for the mating pool was found to work very well. Crowding metric helped to maintain diversity and thereby better spread in the Pareto front.

From this Pareto set, one can choose an operating point based on different kind of requirements of the plant. If quality is a primary issue where relatively more of coke consumption is allowed, one can choose a point from the given Pareto set that has a higher SQM as well as C_W value. Had coke consumption been little more important than quality, under some circumstances, the reverse of the same proposed earlier is done.

Furthermore it has been analyzed whether the location of the global Pareto front changes with different heights of the sinter bed. As the total sinter bed height was varied from 30 to 60 cm, with a gap of 10 cm, the global Pareto front in each case were found to get a push towards right bottom corner of fig 6. It was further observed that increasing the bed height any further is not going to help as the global Pareto fronts for total bed height of 50 and 60 cm were almost identical or very close to each other. A bed height of 50 to 60 cm was, therefore, recommended. Increase in bed height will require higher suction pressure, which generally restricts the bed height, and a comparison between the suction pressure for the different bed heights and the corresponding burn through points (BTP) are given in table 2.

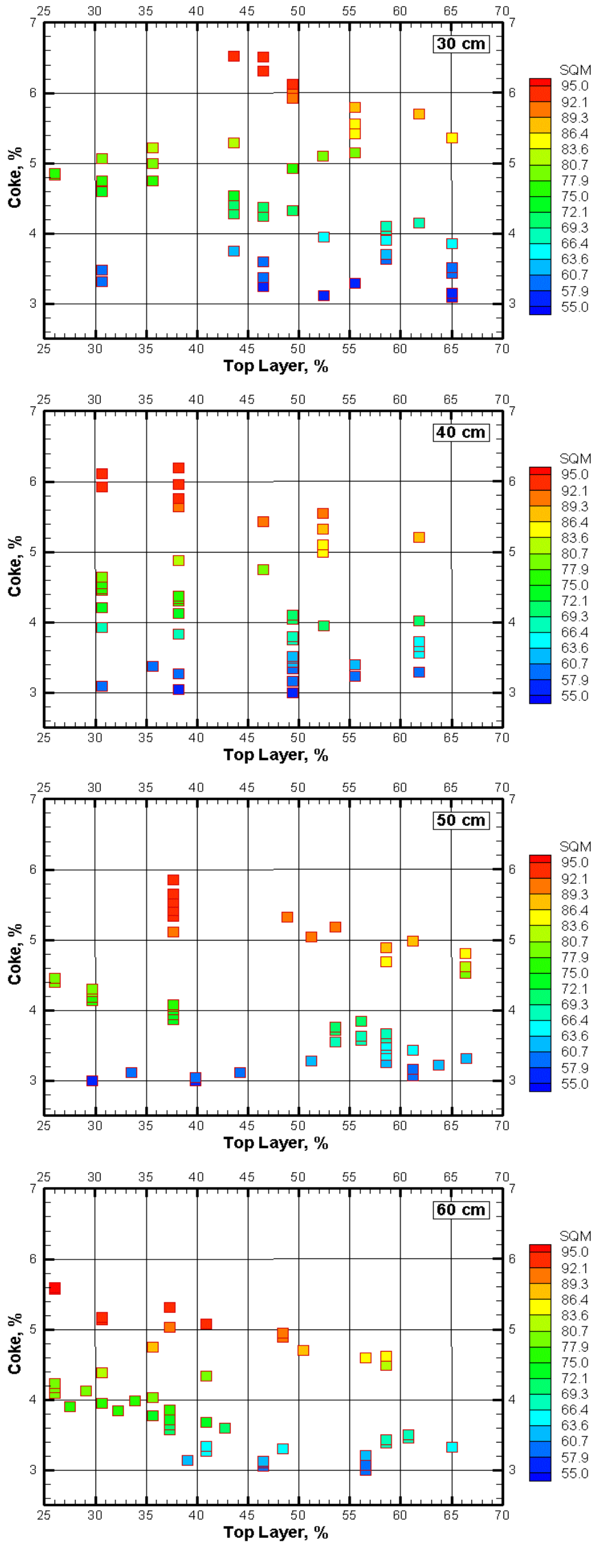

Fig. 7. Pareto points in top layer vs. coke rate domain, for 30, 40, 50 and 60 cm bed height.

Table 2. Suction pressure applied for different sinter bed heights

Bed Height cm	Ignition Hood 0-4 min	Top 4-6 min	Middle & Bottom 6-15 min	BTP Min
30	750	750	1000	12.5
40	1000	1000	1300	15.0
50	1250	1250	1600	17.0
60	1500	1500	1900	19.5

We can now redraw the same Pareto optimum set points shown in fig. 6, separately for the four different bed heights by adding another dimension to it, i.e. the top layer thickness as shown in fig 7. By comparing the four graphs for the four different bed heights, some general trends can be observed, which gives a very good insight of the process. The top layer thickness (as percentage of the total bed height) gradually decreases with increasing total bed height. For example the Pareto points for 30 cm bed height with high SQM (~ 95 %) and low coke rate lies between 45-50 % top layer thickness, while for 60 cm bed height it is scattered mainly between 30-40 % top layer thickness. There is also a gradual shift of the Pareto points from the high coke rate region to the low coke rate region as the bed height increases, and for comparative study we can observe that for 30 cm bed height, points with high SQM value needs about 6 % or more coke rate, and for 60 cm bed height similar SQM value can be achieved with about 5 % coke rate. Therefore we can conclude that coke rate can be reduced by about 20 % when sinter bed is increased from 30 to 60 cm. Analysis of two-layer sintering process by Pareto optimum points shown in fig. 7, can be an ideal tool to evaluate the most suitable operating point with respect to sinter quality for melting, coke rate and top layer thickness, for an existing sinter plant under the given constrains, or for designing new sinter plants.

The NSGA II parameters used to obtain the Pareto set for the present study are as follows: Population size = 50; Number of decision variables = 3; String length for each decision variables = 6; Maximum number of generations = 30; Crossover probability = 0.9; Mutation probability = 0.01; lower bounds used for coke in upper and lower layers = 3 %; upper bounds used for coke in upper and lower layers = 10 %; lower and upper bounds used for the top layer thickness are 25 % and 70 % respectively.

6. CONCLUSIONS

The salient points of the present study on multiobjective optimization of two-layer sintering of iron ore can be summarized as:

1. A twin objective optimization problem relating quality and fuel consumption issues for iron ore sintering operation is solved using NSGA II. The problem displayed a convex Pareto-optimal front.
2. NSGA-II has been able to find solutions on or near the true Pareto-optimal front of the problems. This has been validated by solving the multiobjective problems using a single-objective preference based optimization method (ε-constraint method) as well as getting the same global solution by starting with different initial population. The other advantage of using the NSGA-II is that it has found multiple Pareto- optimal solutions in a single simulation run.
3. The optimum top layer thickness is higher in the range of 45-50 % for low sinter bed height of 30 cm and gradually decreases to 30-40 % top layer thickness for high sinter bed height of 50-60 cm.
4. This study suggests that the effect of increase in bed height is more significant in the lower bed height region of 30-40 cm, and becomes less significant as the bed height increases from 50 to 60 cm, and any further increase in bed height will not provide much improvement in Pareto front.
5. About 20 % reduction of coke rate is expected when bed height is increased from 30 to 60 cm for achieving similar high sinter quality of melting.

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8. NOMENCLATURE

d_p	Granule diameter, m
Fm	Fraction melted, %
L	Height of bed, m
P	Pressure, atm
R_i	Reduction rate, mole / s
V	v / vo non-dimentional gas velocity in y direction
V_s	vs / vo non-dimentional solid velocity in x direction
x, y	Direction co-ordinate, m
X	$(C_s^o - C_s)/C_s^o$, solid fraction converted
μ	Viscosity of gas, Kg/m.s
ρ	Density, kg/m^3
ε	Bed porosity