Production of Low Phosphorus Steels and Ensuring Direct Tap Practices for the BOF Steelmaking Process

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Keywords: dephosphorization; oxygen steelmaking; process control.

1. Introduction

The partition ratio of phosphorus between slag and steel in the BOF is conventionally defined as following: $L_P = (\%P)_{slag}/[\%P]_{metal}$. The main factors which are incorporated in various models[1-6] reported in literature are temperature, basicity of slag and the FeO content. Of these, the temperature is seen to have the largest influence. These models are applicable, in principle, when a single liquid phase is present. In actual practice the slag is a multiphase multicomponent system with varying proportions of solid and therefore the adaptation of all the models to the operating practice is essential. There are conflicting views whether equilibrium is established or not at any stage of blowing in BOF. In recent investigations it has been reported that di-calcium-silicate $2CaO.SiO_2$ (C_2S) and tricalcium phosphate ($3CaO.P_2O_5$) form 100% solid solution at steelmaking temperatures[6]. Therefore, the slag containing solid di-calcium-silicate can dissolve a high amount of phosphorus in liquid slag[7-8]. According to Inou and Suito[7] dephosphorisation becomes favourable with increasing the solid/liquid ratio in the coexisting phases compared with the dephosphorisation with liquid slag only for a given flux consumption.

Practical observations made during the plant trials conducted in this work have confirmed that both the initial part of the blow and the end part of the blow are equally important to obtain high L_P values. In this work, industrial data are analyzed by employing a post-combustion control dynamic model for the early and the middle parts of the blow. A control strategy for the middle blow period is suggested. For the end blow predictions the multivariate regression method, based on thermodynamic relations proposed in literature and also the Mahalanobis Taguchi Systems (MTS) are employed to identify the most important or significant variables affecting phosphorus distribution. The selected variables are also used to develop Artificial Neural Networks (ANN) for the prediction of phosphorus contents in steel at the end. Efficacy of all the techniques is compared.

2. Control of phosphorus distribution during the early and middle blow periods through post combustion model

Plant trials in the present work have shown that the post-combustion control can be used as a tool to control the path of slag formation during the early and the middle blow periods.

As reported earlier, a dynamic control model has been developed[9]. In addition to this a post-combustion model has been developed to predict the post combustion ratio at the mouth of the converter. The predictions of the post combustion model are compared with the waste gas information available on-line. Coupled analysis of post-combustion ratio in association with the oxygen blowing lance height, lance water temperature, waste gas flow rate, oxygen flow rate and the estimated FeO level of the slag help to identify the dry blow in advance. A dry blow period will occur if the trend in the blow is towards a lower value of post-combustion ratio and lower FeO content of the slag than specified for a particular heat. Based upon this advance prediction, substantiated by dynamic or on-line measurements of waste gas parameters during the blow, a corrective action is automatically taken or suggested to the operator to avoid the dry blow period and to improve the dephosphorisation performance. In this way the behaviour of slag formation can be controlled using post-combustion as a guiding tool.

2.1 Control and prediction of dry blow period

The dry blow happens due to the fast reduction of FeO in the slag and simultaneous precipitation of solid component (C_2S), which can be calculated at very time step from a dynamic model. An on-line mathematical model has been developed to predict the state of the process in terms of metal and slag compositions and weights, proportion of the solid and liquid slag and undissolved components along with the decarburization rate profiles[9]. The dynamic predictions, generated online, during the blowing process guide to detect and decide the occurrence of dry slag formation in advance. Once the dry slag formation is predicted then an appropriate action follows regarding the change in the lance height as a first option. In a more severe case of deviation from the desired path the oxygen flow is reduced or increased (maximum by 15%) till the process returns to normal expected state in the subsequent stages of the blow. It should be the noted that the response time of the BOF process is around 30 seconds for any change that is made in oxygen flow rate or lance height, if that has to be decided from the on-line measured parameters vis a vis the model predictions.

2.2 Optimal process control strategy in the middle blow period

Every heat in BOF poses a new challenge for control and no predetermined standard lance height and oxygen flow rate profile can be decided in advance. It has to be done on heat to heat basis. In most plants it is a practice to evolve a set of blowing profiles (combination of lance height and oxygen flow rate adjustment patterns) depending upon the grade of steel, quality of hot metal, and scrap parameters, viz silicon content of hot metal, quality of scrap, scrap to hot metal ratio, hot metal temperature etc. It is however also well accepted that the BOF process is not a deterministic process. It is part deterministic, part stochastic and part chaotic. It is the stochastic and the chaotic components together which drive (or forcefully try to navigate) the process along a different temperature and composition paths in each blow. Therefore on-line adjustments or changes have to be decided in each heat as the blow progresses. It is this aspect which makes the dynamic control of BOF both interesting and challenging. A prior practical experience of handling the process on the shop floor is perhaps necessary to understand the different facets of manifestation of chaos. This understanding is certainly required if a successful dynamic control model is to be developed and implemented.

In the control strategy developed in the present work, on the basis of the measured and calculated dynamic process parameters a decision table is constructed and evaluated every 30 seconds. For example the decision table generated at 180 seconds is described in Table. 1. The parameters considered in the table and the relative weights assigned to the different parameters change with time and are decided by careful plant trials on the shop floor. The most important part of implementaion of such a model is operator training because in about 40% of the cases the operator may be asked to choose/approve the action suggested by the model. BOF process is about 20% chaotic in nature and hence manual intervention/approval becomes necessary for the sake of safety. The positive side is that with this approach it has been possible to avoid dry slag formation in 100% of the cases. In one case, the trials are being made where sub-lance is used and the objective in this plant is to avoid the use of sub-lance altogether by guaranteeing that the dry slag formation will not take place, specially for heats with medium or non-critical phosphorus target at the end point. It has also been possible to overcome the inconsistency in blowing related to slag splashing and quantity of slag retention in the vessel because large slag volume changes the post combustion pattern. Avoidance of dry slag formation alone may lead to reduction in iron fume losses by about 5-20 kg/ton of hot metal in a particular heat. The main advantage is of course a better end point phosphorus, carbon and temperature control and drastic reduction in the re-blows.

As a post mortem analysis, SEM micrographs were also analyzed for selected heats. The samples were collected from the lance skull at different moments of blowing. Analysis of these samples has shown that the di-calcium-silicate has the highest capacity to retain P_2O_5 (up to 6% mass). Slag saturated by CaO preferentially precipitates C_2S in later stages as well. Therefore controlling the slag path which gives a high C_2S proportion is desirable for producing ultra-low phosphorus steels. Obviously, MgO does not help in the precipitation of C_2S.

3. Phosphorus prediction at the end of the blow

Both, the multivariate regression analysis and the Mahalanobis Taguchi Systems (MTS)[10], are used in this work to predict phosphorus contents and compare their efficacy for the conditions at the end of the blow. MTS aided multivariate regression can be a better alternative. The industrial data from three different steel plants (Table 2) in India are analyzed in this work.

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4. Results of multivariate regression analysis, MTS method, and artificial neural net (ANN)

The details of different parameters, in alphabetical order, are as follows: BASICITY = CaO/SiO_2 ratio of slag, CAL_DOLO = weight of calcined dolomite in tons, DOLO = weight of raw dolomite in tons, (FeO) = FeO % of end slag, HMA_P = % phosphorus in hot metal, IRON_ORE = iron ore added, LIME = weight of lime in tons, (MgO) = MgO % of the slag, OXY_ACT = oxygen blown, (P_2O_5) = P_2O_5 % of the slag, SCR = scrap charged in tons, SI_HM = silicon % of the hot metal, TAPTEMP = end temperature of steel, T_HM = temperature of hot metal, WT_HM = hot metal weight.

For Plant A, the multivariate regression analysis gives the following equation with R-Square = 0.38, Standard Error = ±0.002

Table 1: Typical decision table generated and evaluated after 180 second of blow time

parameter	Variation from expected	Advice for lance height	Advice for Oxy flow
Waste gas flow	No	Lower	Increase
Water ΔT.	Yes	Raise	Decrease
Gas CO%	Yes	Raise	Decrease
ΔT versus CO%	Yes	Raise	Decrease
Post comb.	No	Raise	Decrease
Final decision		Raise by 10 cm	Decrease by 20 m^3/min

$[P]_{end}$ = 1.03e-4 SCR – 1.208 OXY_ACT + 8.11e-5 TAPTEMP - 1.24e-3 BASICITY - 0.111

In the MTS run the following variables were selected (variables with the positive gain value are selected): HMA_P, HMA_TEMP, WT_HM, OXY_ACT, TAPTEMP, FeO, P_2O_5, BASICITY. Subsequent regression analysis on the selected variables gives the following equation with R-Square = 0.39, and Standard Error = ±0.002

$[P]_{end}$ = 3.25e-4 LIME – 4.15e-5 WT_HM + 7.48e-5 TAPTEMP – 1.74e-3 BASICITY – 0.095

Neural Network 4-7-1 was also tried on the variables selected by MTS. Results are not better as compared to the regression method. (R-Square=0.317)

Table 2: Parameters of different plants investigated in this work

Parameters	Plant A	Plant B	Plant C
Heat Size (Tonns)	150	150	140
Si% in HM	0.4-0.5	0.6-0.8	0.4-0.6
Taget [P] (%)	0.010-0.020	0.020-0.050	0.020-0.040
P % in HM	0.10-0.15	0.15-0.25	0.10-0.20
Slag FeO (%)	15-20	18-25	18-25
Slag Basisity	3.0-4.5	2.5-3.5	3.0-4.0
Tap temperature	1660 C approx.	1660 C approx	1700 C approx

Analysis of the correlation matrix revealed the following. $[P]_{end}$ has the strongest correlation with TAPTEMP, medium correlation with LIME and IRON_ORE and week correlation with the rest of the variables. LIME is strongly correlated with WT_HM, SCR, HM_SI and ORE. It has medium correlation with $[P]_{end}$, HMA_TEMP and FeO. IRON_ORE is strongly correlated with OXY_ACT, LIME, SCR and WT_HM and medium correlated with the rest. TAPTEMP is strongly correlated with $[P]_{end}$. It has medium correlation with OXY_ACT and having week correlation with the rest. The analysis of the correlation matrix showed that MTS was successful in selection of the most significant variables. For Example LIME has got strong correlation with HMA_SI , WT_HM, SCR, IRON_ORE . WT_HM has got strong correlation with LIME, SCR and IRON_ORE. Therefore just by selecting LIME, WT_HM, TAPTEMP and BASICITY, MTS has taken care of the influence of the most important parameters.

For plant B, the adapted Healy's equation with R-Square = 0.39, Standard Error =± 0.015 is:

$$\ln\left(\frac{P2O5}{[P]}\right) = \frac{20254}{(TAPTEMP + 273)} + 0.3638.\ \ln(FeO) - 0.0499.\ (MgO) - 6.299$$

Multivariate regression analysis gives the following equation with R-Square = 0.25, and Standard Error = ±0.007

$[P]_{end}$ = 2.87e-3 WT_HM + 2.92e-3 SCR – 3.32e-3 IRON_ORE -0.457

In the MTS run the following variables, with the positive gain value, were selected: HMA_P, TAPTEMP, IRON_ORE, MGO, BASICITY. The following results were obtained after performing multiple regression selecting the above variables, with R-Square = 0.38, Standard Error = ±0.007.

$[P]_{end}$ = 1.6e-4 TAPTEMP – 2.29e-3 IRON_ORE -0.235

Neural Network 5-8-1 with was also tried on the variables selected by MTS. Results are not better as compared to the regression method. (R-Square=0.3467)

The study of the correlation matrix showed similar effects as discussed for plant A.

For Plant C, multivariate regression analysis gives the following equation with R-Square = 0.17, Standard Error =± 0.007

$[P]_{end}$ = 1.86e-4 TAPTEMP + 6.43e-5 WT_HM + 1.70e-4 SCR – 1.037e-3 LIME + 8.17e-4 DOLO + 8.31e-5 HM_SI – 4.27e-4 FEO - 2.26e-3 BASISITY -0.284

In the MTS run the following variables were selected: T_HM, TAPTEMP, LIME, CAL_DOLO, IRON_ORE, DOLO, HMA_P. The following results were obtained after performing multiple regression with the selected variables, with R-Square = 0.129, Standard Error = ±0.007

$[P]_{end}$ = 1.96e-4 TAPTEMP – 6.71e-4 LIME + 9.49e-4 DOLO + 3.78e-4 HMA_P- 0.30614725

The study of the correlation matrix showed similar effects as discussed for plant A. The neural network 4-7-1 was also tried on the variables selected by MTS. Results are not better as compared to the regression method. (R-Square=0.127)

To summarize, the results described above for the three plants A, B and C, show that in all the three cases, the MTS method gives a better selection of significant variables and also a better prediction with a smaller number of selected variables. Neural Networks did not improve the predictive performance on the MTS selected variables. If only end point conditions are taken into account then the temperature is the most important variable. Shop floor experiments in the present work have shown that the control of slag formation in the early and middle stages of the blow is more important than simply the conditions at the end of the blow.

5. Conclusions

The slag path can be modified by using the dynamic post-combustion model as a guiding tool. The dry blow period can be avoided in 100% of the cases, thereby making dephosphorisation better. Mid blow control is important for establishing direct tap practices. SEM analysis of the mid-blow ejected slag sample confirms the presence of di-calcium silicate and its high phosphorus capacity. Variable selection approach using MTS method followed by multiple linear regression analysis is found to be more successful than simple conventional multivariate regression analysis. Application of neural networks does not improve the performance on the MTS selected variables. Controlling the slag path in a way which promotes the formation and retention of di-calcium silicate will improve dephosphorisation.

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