Analysing blast furnace data using evolutionary neural network and multiobjective genetic algorithms

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Approximately one year's operational data of a TATA Steel blast furnace were subjected to a multiobjective optimisation using genetic algorithms. Data driven models were constructed for productivity, CO_2 content of the top gas and Si content of the hot metal, using an evolutionary neural network that itself evolved through a multiobjective genetic algorithm as a tradeoff between the accuracy of training and the network complexity. The final networks were selected using the corrected Akaike information criterion. Bi-objective optimisation studies were subsequently carried out between the productivity and CO_2 content with various constraints at the Si level in the hot metal. The results indicate that a productivity increase would entail either a compromise of the CO_2 fraction in the top gas or the Si content in the hot metal. The Pareto frontiers presented in this study provide the best possible parameter settings in such a scenario.

Keywords: Blast furnace, Genetic algorithms, Neural network, Multiobjective optimisation, Pareto frontier, Evolutionary computation, Akaike information criteria

Introduction

The blast furnace process, owing to its high degree of non-linearity and random fluctuations, is not convincingly amenable to mathematical models, although quite a few have been tried out in the recent past.[1,2] Many such analytical models utilise the basic principles of thermodynamics and transport phenomena to explain the highly complex process of blast furnace iron making, and attempt to solve the system equations numerically. Such models, so far, have met with a limited success, and in fact, only some idealised cases can be actually studied using them, while the response of an industrial blast furnace could be much noisier than any such model predictions.

In addition, determining the accurate values of the model parameters remains a major bottleneck for capturing the actual physics of the process through thermodynamic or transport equations, and a far more reliable strategy would be to come up with a blast furnace model utilising the long term operational history of a furnace, for which several strategies are now firmly in place. Construction of such data driven models based upon a strategy, like the artificial neural networks,[3] although an effective and rational approach, is not free from potential sources of error as blast furnace data are not only non-linear but also significantly noisy.

Any attempt of model construction in this scenario is rendered complicated by the difficulty of assessing the right complexity for the model. A highly complex model would be difficult to execute and might overfit the data. Such networks would tend to capture the noise in the data set, treating them as real trends. Conversely, if the complexity of the model is below a threshold level, it would underfit the data, and the network will fail to capture the basic trends of the process. The task of coming up with a neural network that would neither overfit nor underfit a blast furnace data would involve a very complicated decision making process regarding the topology of the network, which, in many real situations, the conventional forms of neural networks might not be able to accommodate.

With the advent of genetic algorithms[4] and particularly their multiobjective adaptations,[5,6] which are now very significantly used in the materials domain,[7–14] the task of coming up with an optimum topology for a neural network dealing with noisy data has become more of a tractable problem. In recent years, the authors have proposed the concept of an evolutionary neural net that evolves the optimised network architectures as a tradeoff between the complexity of the model and the accuracy of training.[15] Subsequently, the method has been further refined through the introduction of some information criteria, namely the Bayesian, Akaike and corrected Akaike,[16–18] enabling it to identify the most suitable network for the system out of several alternates.

In this study, about a year's data from a TATA Steel blast furnace have been trained using an evolutionary

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network strategy, followed by multiobjective optimisation through genetic algorithms. The pertinent details are presented below.

Optimisation problem

Objective functions representing the productivity and the percentage of CO_2 in the top gas were selected during this study, and two bi-objective optimisation tasks were performed with various levels of constraints on the Si content of the hot metal.

The bi-objective optimisation task taken up in this study was to minimise percentage of CO_2 in the top gas while maximising productivity, subject to a prescribed range of Si content in the hot metal.

Here, the prescribed objectives are conflicting: any improvement in one would lead to deterioration in the other. This leads to a well known Pareto optimal problem,[5,6] where no unique optimum can be found, and the optimum is represented by a set of solutions, the members of the Pareto optimal set,[5,6] denoting the best possible tradeoff between the objectives.

The objective functions were constructed using an evolutionary neural network approach,[15] which itself evolved through a multiobjective genetic algorithm. The subsequent optimisation tasks were carried out using a predator–prey genetic algorithm used extensively in our earlier studies.[15–18]

Formulating objective functions and constraints

The data from the blast furnace, expectedly, were quite noisy. The initial task was to prune the obvious outliers and to do some limited interpolations in some cases where the observations were quite sparse. For each objective, several models were constructed: one with the entire data set and the rest using some overlapping subsets of it. The models constructed with one data set were also tested on the others, in order to ascertain the reliability of the models and the associated interpolations. A total of nine physical variables were considered in this study; each, in turn, was considered for three consecutive time steps, t, $t-1$ and $t-2$, resulting in a total of 27 variables. This time lag was incorporated into any temporal data to capture the effects of the long residence time of materials processed inside the furnace. The nine physical variables were related to the objective functions as follows:

(i) productivity: function of coal injection, coke rate, ore/sinter ratio, input basicity ratio of charge, blast pressure, blast temperature and oxygen enrichment

(ii) top gas CO_2 (%): function of coal injection, coke rate, blast pressure, blast temperature and oxygen enrichment.

The constraint function was constructed as percentage of Si in hot metal: function of coke rate, coal injection rate, percentage of coke ash, percentage of coal ash, oxygen enrichment, blast temperature, input basicity ratio of charge and ore/sinter ratio.

In the course of this work, the authors also attempted to construct a model for the slag bulk as a function of percentage of coke ash, percentage of coal ash, coke rate, coal injection rate, ore/sinter ratio and input basicity ratio of charge. The slag data available in hand, however, was quite sparse, and the model turned out to be less accurate. The slag analysis therefore is not reported here.

In order to maintain continuity in the data time series during final optimisation, a maximum perturbation between two consecutive time steps was specified for each variable. The input basicity ratio of the charge was computed as the ratio of the sum of the weights of $(CaO+MgO)/(SiO_2+Al_2O_3)$ both from the sinter and lump ore. The authors' sample calculations indicated no major differences in results when the molar ratios were used instead. The other variables are used in the conventional sense, as described in the standard blast furnace literature.[19]

The training process of the objectives and the constraints are elaborated below.

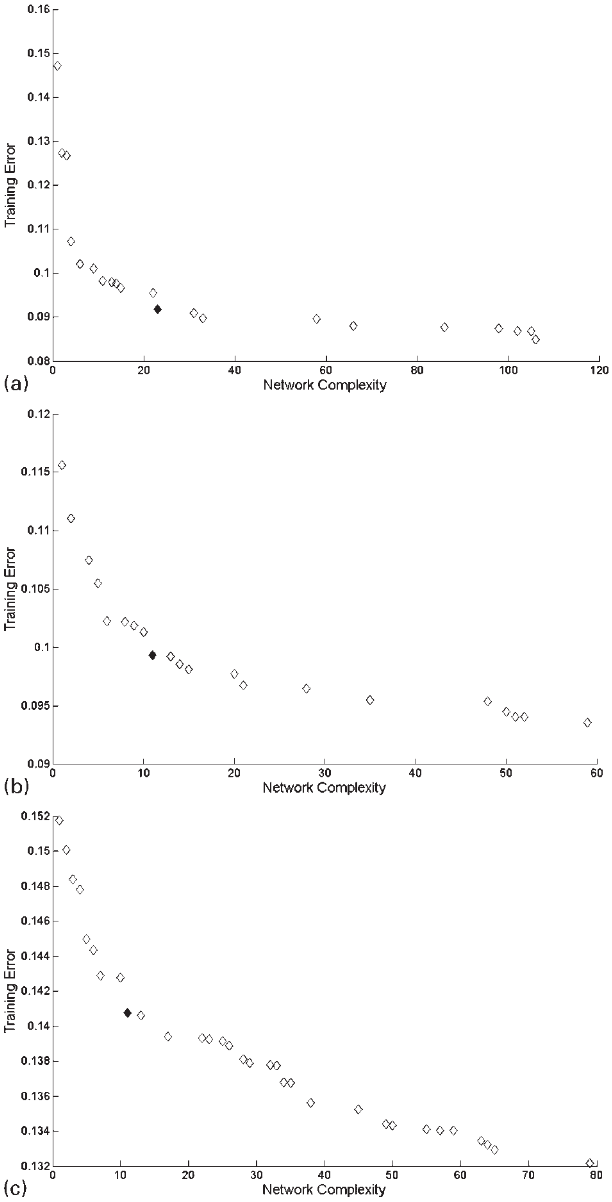
Training of objective and constraint functions

Feedforward neural networks of the multilayer perceptron type, with a single hidden layer of sigmoidal units and a linear output layer, were used as models for the objective and the constraint functions. The weights in the lower layers were evolved by the multiobjective genetic algorithm, simultaneously determining the optimal upper layer weights by the linear least square method. This yielded their respective Pareto frontiers,[5,6] consisting of the best tradeoffs between the dimensionless training error and complexity of the model, expressed in terms of the total number of connections in the lower part of the network, excluding the biases. Complexity, thus, is expressed as an integer.

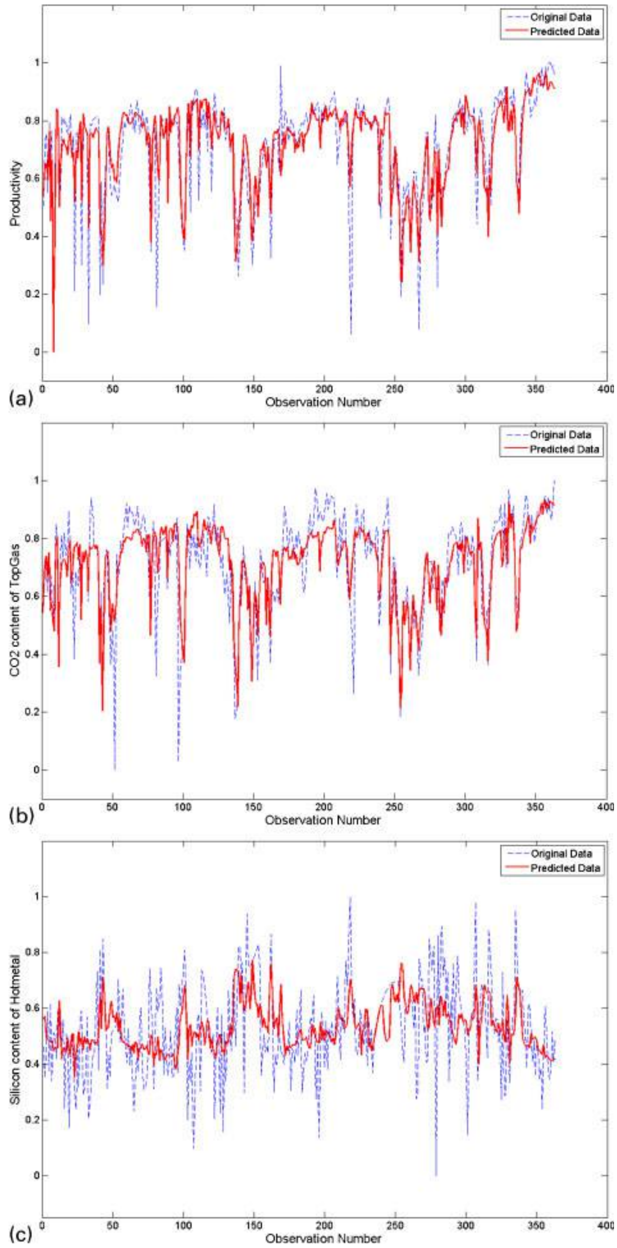
In Fig. 1, the results are presented for the networks using the complete data set, formed after removing the outliers and generating information through limited local interpolation, as and when needed. Each point in these figures denotes a specific neural net of unique architecture, and the darkened diamonds denote the neural network chosen on the basis of the corrected Akaike information criterion (AICc),[16–18] the procedure for which is elaborated in earlier publications.[16–18] In this case, the finally accepted Pareto frontiers had emerged after some systematic numerical experiments with various random number generating techniques and their initial seed values.

Using a similar strategy, a number of other networks were constructed for each objective and the constraint, using some intersecting subsets of the entire data set and mutually tested on each other. The results are shown in Table 1. Here, the complete data set is denoted as 'data', and the network constructed using it is denoted as 'Nnet', and a typical network 'Netj' is trained using 'dataj', a subset of 'data'. The total number of such subsets was taken as three for each model. Any number in this table would indicate the error of using its corresponding data set on the corresponding network. Thus, 0·0852, the first number in the 'Productivity' part of the table, is indicative of the performance of 'Net1' on 'data1'.

All these error values are acceptably small, showing evidence of reasonably reliable training and interpolation. Performances of various networks constructed with the complete data sets are shown in Fig. 2. Only normalised values calculated using the maximum ranges



1 Pareto frontier of networks trained for *a* productivity, *b* percentage of CO_2 in top gas and *c* percentage of Si in hot metal (darkened point denotes network selected based on Akaike information criterion)



2 Performance of evolutionary neural net selected for *a* normalised productivity data, *b* normalised top gas data and *c* normalised data on Si content of hot metal

Table 1 Performances various networks on different data sets: numbers indicate training errors

	Data1	Data2	Data3	Data
Productivity				
Net1	0·0852	0·1023	0·1178	0·1076
Net2	0·1218	0·0993	0·1139	0·1219
Net3	0·1357	0·1132	0·0731	0·1127
Nnet	0·0930	0·0982	0·0868	0·0919
Percentage of CO_2 in top gas				
Net1	0·1157	0·1150	0·0969	0·1088
Net2	0·1314	0·1115	0·1023	0·1216
Net3	0·1691	0·1140	0·0903	0·1405
Nnet	0·1111	0·1076	0·0830	0·0993
Percentage of Si in hot metal				
Net1	0·1567	0·1814	0·1883	0·1810
Net2	0·1539	0·1389	0·1364	0·1486
Net3	0·1462	0·1457	0·1374	0·1443
Nnet	0·1363	0·1460	0·1402	0·1408

in the final data sets are presented in these figures to protect propriety information. In each case, the trained networks have faithfully reproduced the basic trends in the data, without showing any evidence of overfitting. For a complicated and noisy data set, like the one in hand, this could be considered as a major success.

In the case of productivity and top gas CO_2 (Fig. 2*a* and *b*), the selected network tends to capture the data trends more closely than in case of Si content of the hot metal, as shown in Fig. 2*c*.

For any blast furnace, Si content of the hot metal is one of the most difficult parameters to control and is often known to vary erratically,[19] partly due to changes in the flow paths and conditions in the furnace hearth, which cannot be measured. It adds to the efficacy of the present evolutionary approach of modelling that it has correctly learnt to ignore the extreme fluctuations in the Si data, leading to a model far more reliable than it

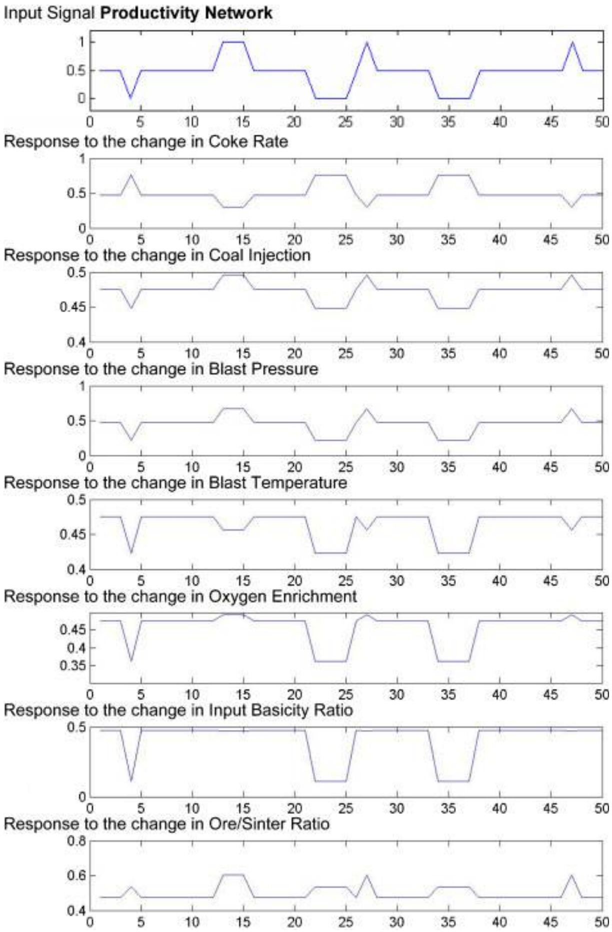
3 Correlation between input variables

would be possible to do otherwise, using a conventional type of neural network.

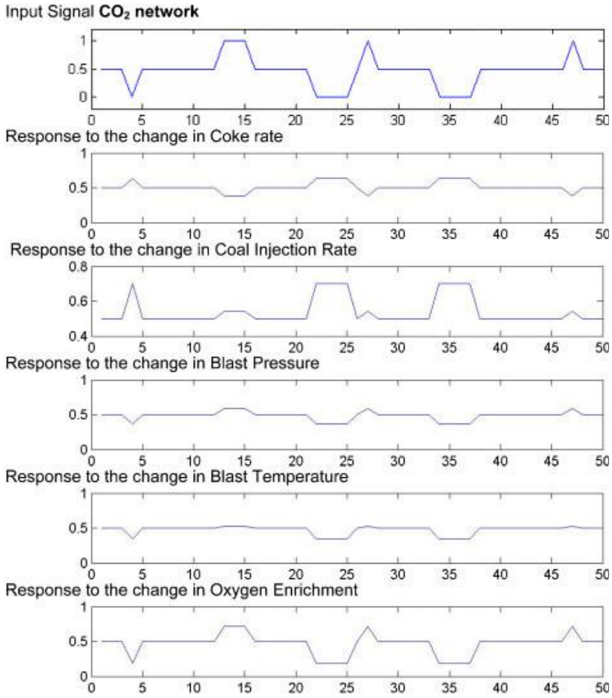
Interaction between variables

Expectedly, among the nine physical input variables, some are independent and some not. Information regarding the nature of this interaction is often crucial for setting the operational parameters of the actual operation and also to explain the complex processes that influence a constraint or an objective function. Approximate but comprehensive information of such interactions is provided in Fig. 3, where any variable pairs of the data set have been plotted against each other, and a linear least squares fit has also been provided. Thus, a horizontal fitted line through the data would suggest no correlation, and a direct or an inverse correlation will depend upon the positive or a negative slope of the fitted line.[12]

The figures, for example, show the strong connection between the blast oxygen enrichment and coal injection and coke rates, which arises since an increase in the coal injection rate is realised by a simultaneous increase in the oxygen enrichment, and the replacement of coke by coal leads to a negative correlation between these two variables. Another notable trend is the positive correlation between blast pressure and oxygen enrichment. Since oxygen enrichment principally reflects the coal injection rate, and a higher coal injection means a lower coke rate, the gas permeability decreases and the pressure loss increases with a higher ore/coke ratio in the lumpy and cohesive zones. In summary, there seems to be no variable that is totally independent of the others, except for the input basicity ratio, which is weakly correlated to most of the variables. This leads to a very complicated scenario, which also gets carried over to the objective and constraint space as well.



4 Impact of various input signals on productivity



5 Impact of various input signals on the top gas CO_2

Role of individual variables

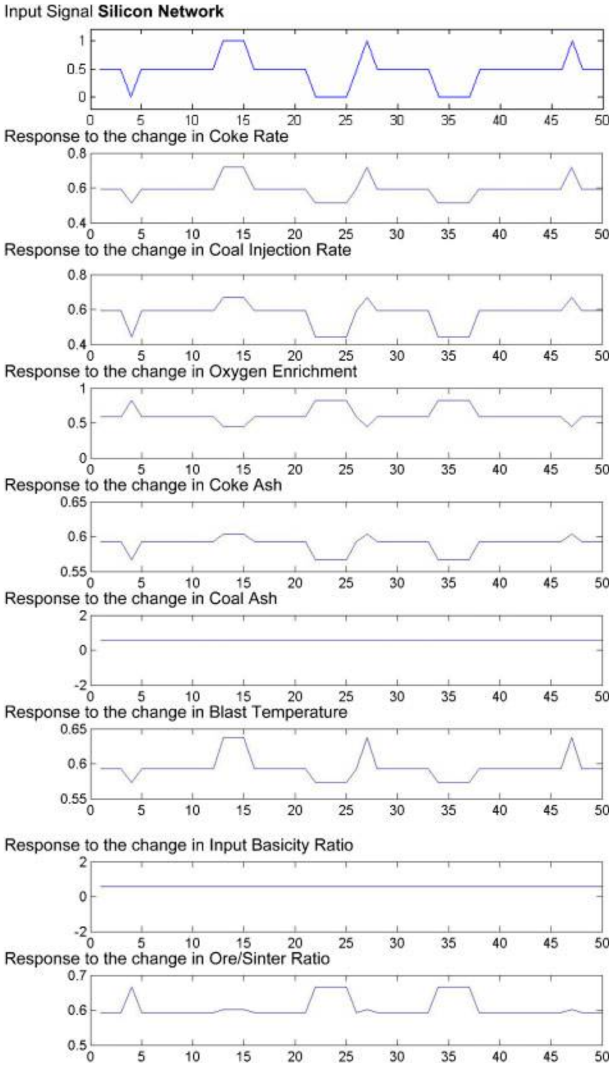
Following the procedure applied in an earlier work,[12] the role played by the individual variables in altering the magnitude of the objective functions and the constraint was analysed by perturbing one input in turn, keeping all other variables fixed. Figure 4 presents one such numerical experiment on the productivity network. Here, the top panel shows a prescribed pattern of variation for an individual variable, coke rate for example, containing regions of sharp increase or decrease, in addition to regions of steady values. Since our neural network used values scaled between 0 and 1, numerically, that fixed level was taken as 0·5. The lower panels in the figure show the corresponding changes in the predicted productivity values. The numbers shown along the x axes are just identifiers for the synthetic data points created for this purpose.

A careful examination of this figure reveals that with an increase in coke rate, the productivity tends to go down and vice versa. It is well known that in an industrial blast furnace, the productivity is directly proportional to the amount of coke burned per day Q and is inversely proportional to the amount of coke consumed per ton of hot metal K.[19] The increasing coke rate results in an increase in K, and the model correctly predicts that, in such a situation, the productivity would go down. With increasing coal injection and also at increasing blast pressures, productivity goes up, and the response to a change in blast temperature or in the level of oxygen enrichment is more or less similar. These are again some highly expected trends. Lowering basicity in the burden affects productivity in an adverse way. It is well known that softening, swelling and breakdown of ores and sinters inside the furnace would affect the bed voidage, which in turn would restrict gas flow and cause loading and flooding of slag inside the coke grid, and the productivity would go down.[19] An increase in basicity is known to counter that effect by significantly preventing sinter breakdown, which is also corroborated by the trends of the models constructed during this study.

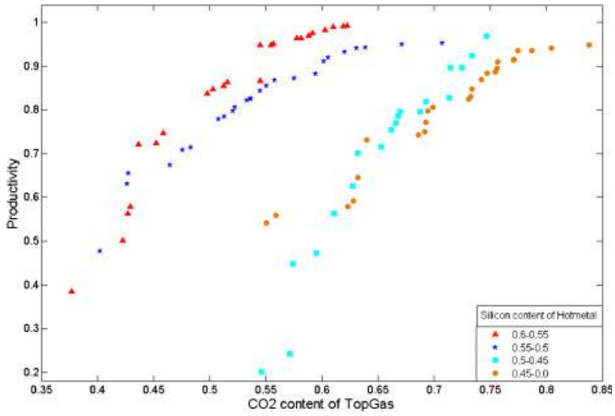
The response of productivity on the ore/sinter ratio is, however, not definitive. As shown in Fig. 3, the ore/sinter ratio is strongly correlated to a number of other parameters, like coke rate, coke ash, blast pressure, etc., which prevents analysing its impact in isolation.

Similar analyses were performed for the CO_2 network, as shown in Fig. 5. The coke rate response on the top gas CO_2 is very similar to the response found for productivity and, in fact, directly related to changes in it. It is, however, difficult to isolate a direct correlation between the coal injection and the top gas CO_2, as coal injection is very strongly correlated with a number of other input variables shown in Fig. 3. This may also be due to the fact that the replacement ratio of (carbon in) coke by coal is close to unity. An increase in any of the three remaining variables, blast pressure, blast temperature and oxygen enrichment, would directly affect productivity and consequently release more CO_2 at the exit. These trends are correctly picked up by the network responses presented in Fig. 5.

The analyses for the Si network are presented in Fig. 6. The model shows that both coke rate and coal injection rate directly affect the Si content in the hot metal, presumably by altering the thermal status of the process and also causing a change in the siliceous material input. Si in the iron generally increases with an increase in the metal temperature.[19] A change in the coke ash also directly affect the Si content, most likely



6 Impact of various input signals on Si content of hot metal



7 Pareto frontiers for minimisation of CO_2 content in top gas and maximisation of productivity at various Si contents of metal: results are plotted in normalised manner in order to protect propriety information

by altering the slag viscosity and changing the slag volume.

The basic oxides like MgO are known to lower slag viscosity as well as the liquidus temperature,[19] permitting efficient Si transfer to the slag phase. Additional siliceous material input through increasing ash content would hamper such transfer processes, and the coke ash in this case is actually rich in such material. In general terms, barring a few negligible exceptions, increasing the ore/sinter ratio seems to decrease the Si content in the metal and vice versa. Unlike the sinter, the ore adds only SiO_2 and Al_2O_3 and no basic oxides, thus providing no advantages in terms of basicity.

Alteration of basicity in such cases might have been brought out in the plant by altering the amount pyroxenite or quartzite charges. For this, however, no specific data are available, and, hence, no definite conclusions could be made. Furthermore, this effect could be very well due to a change in the bed permeability affecting the diffusion of SiO and SiS vapours through the lower part of the burden that plays a crucial role in Si transfer. With increasing oxygen enrichment, the Si content of the metal decreases, owing to an increased production of SiO vapour at higher oxygen potential, which could not be reduced at the tuyere level, where, as per the literature evidence, the SiO reduction predominantly takes place.[19] Furthermore, the reduced volume of gas with lower N_2 content that forms during oxygen injection cools down more rapidly from the raceway adiabatic flame temperature, so the residence time of the iron droplets in the high temperature region is also decreased, and it significantly affects the Si transfer process.

The model could not pick up any impact of the injected coal ash or the input basicity on the hot metal Si content.

Multiobjective optimisation

Using the models evolved for the objective and constraint functions, the results of two bi-objective optimisation studies conducted through a predator–prey genetic algorithm[15] are shown in Fig. 7. Here, the Pareto frontiers are presented for a simultaneous minimisation task of the CO_2 in the top gas along with a maximisation of productivity. The reported values are once again normalised against the maximum productivity (t/m^{-3}/day) and thus scaled between 0 and 1 to protect propriety information. The Si contents of the metal are constrained at different ranges, as shown through different symbols. Among the non-dominated points[5,6] along the frontiers, the selection of the actual operating point would be a decision maker's preference. The results directly establish the conflict between the top gas CO_2 and productivity, and the Si content in the hot metal is in conflict with each of them. Therefore, productivity can be increased only by compromising the CO_2 fraction in the top gas or the Si content in the hot metal. The optimum tradeoffs in such a scenario are, however, directly available from Fig. 7.

Conclusions

A trained evolutionary neural network, as constructed in this study, can be used as a predictive tool for estimating the expected performance of the blast furnace, with periodic variation of the input parameters. Coupled with an optimiser, it becomes a handy tool for performance enhancement, which the operators can try out rather routinely before implementing any changes in the operating conditions. Although we have not yet used the models presented in this paper as a predictive tool for the relevant blast furnace at TATA Steel, it is expected to have that capability, and actual plant application remains a future direction for our research.

Despite a high level of noise and significant sparsity in the available information, the evolutionary multiobjective approach adopted in this study could provide some significant insight of an operational blast furnace of a major integrated steel plant. Although the efficacy of neural networks and time series analysis are already appreciated in blast furnace modelling and other iron making processes,[11,20–22] the complex and often a bit erratic processes like Si transfer can be analysed more convincingly by bringing in the concept of Pareto optimality. The methodology is demonstrated in this work.

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