Conventional and AI Models for Operational Guidance and Control of Sponge Iron Rotary Kilns at TATA Sponge

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Abstract: Prediction models for temperature, pressure and quality control in rotary sponge iron kilns are developed from operational data. The conventional and AI based methods which are used to develop the models include Extreme Learning Machine (ELM), Artificial Neural Net (ANN) and Multiple Linear Regression (MLR). The performance of the developed models is tested on shop floor in actual operation and compared. Extensive plant data are used to develop and validate the models on day-to-day basis of operation so as to take care of the dynamically changing situation inside the kiln, giving first preference to quality control and then to accretion control. Accretion control increases the life of lining and thus also the available time for production. Automatic pressure control greatly helps in chaos control inside the kiln. Dynamically changing Lyapunov exponent acts a guide line for automatic pressure control.

Keywords: Rotary Kiln, Sponge Iron, Operational Control, AI models, Chaos Control

1. Introduction

TATA Sponge employs coal fired rotary kilns to produce sponge iron. Iron ore, coal and dolomite are charged from one end of rotary kiln (schematic diagram in Fig. 1) and the coal for combustion is fired from the other end. Rotary kiln is slightly inclined so that material flows in forward direction. Partial combustion of coal is assisted by the air blown through primary air blower and root blower from firing end and, in addition, several secondary air blowers are suitably placed along the entire length of the kiln. The rotary kiln is a counter current reactor (opposite movement of charge and air). PID controllers are used to maintain desired pressure difference between inlet and outlet gas pressure inside the kiln. The reducing gases produced inside the kiln need to be maintained within a desired window of temperature, pressure and composition range to enable optimal reduction of iron oxide to iron. The degree of reduction of iron oxide to iron is one of the key quality parameters for deciding the selling price of sponge iron in the market. Several research papers on sponge iron production in rotary kilns have been published describing both heat and mass transfer aspects as well as expert systems based on fuzzy logic and ANN.

The earlier work [1] on mathematical modeling of heat and mass transfer in rotary kiln helped to predict the concentration and temperature profiles inside the kiln. A series of research publications following the same line of approach [2-3] finally culminated in [4] in which some suggestions were made regarding optimum steady state operability of kiln. Process control of kiln cannot be achieved by heat and mass transfer based models alone. The main reason is that the fluctuations inside the kiln are chaotic whereas the earlier researchers assumed convective flow conditions. Recent approaches are based on fuzzy logic [5-6] and ANN [7-8] to take care of non-linear phenomenon inside the kiln. The aspect of constant presence of chaos inside the kiln has still eluded these researchers, hence efficient accretion control as well.

Chaos, by definition, is bounded and control schemes can be devised for obtaining the results within a desired window in the presence of chaos as well. In the present work it is shown that control of chaotic variation of pressure variations inside the kiln is the first requirement of accretion and quality control, in addition to kiln rotation speed, feed rate of ore and coal, and the quality of raw material (ash content of coal and percentage of fines in ore and coal). The heat and mass transfer models are still needed because they help to decide the basic mass and thermal requirements of kiln but the control of rotary kiln, so as to minimize accretions and maintain quality is much more involved because of the non-linear dynamical nature of kiln reflected in chaotic variation of pressure inside the kiln.

The models developed for the kilns at TATA sponge, along with chaos control procedures, have been embedded in the decision support system of kiln control. The conventional models are developed by using multiple linear regression (MLR) and the AI models are developed by using artificial neural net (ANN) and Extreme Learning Machine (ELM) [9]. Selection of appropriate model to use is made on the basis of its efficacy. A separate routine is implemented for dynamic pressure control. In the present work the aim is to compare the predictive abilities of a combination of AI and conventional models and pressure control in the real life plant environment with an aim of accretion and quality control.

2. Plant Data

A large amount of reliable data is required for developing the conventional and AI models. Plant data is collected (average of eight hours, depending upon nature of data and equation to be developed, but over 30 days) of inlet pressure, outlet pressure, primary air blow rate and secondary air flow rate (in eight secondary air blowers placed along the length, (80+ meters, of kiln), ore and coal charging rate from feed end, coal firing rate from firing end, and temperature measured by ten thermocouples (again, placed along the length of kiln).

Typical values of measured pressure (PR, mm of water column),primary air blown (PAB, m^3 per hour), ore feed rate (ORE, tons per hour), kiln rotation (RPM, rotation per hour) feed carbon in injection coal (FCIC, tons/hour), feed carbon in feed foal (FCFC, tons per hour), air blow through secondary air blower (SAB 1-8, m^3 per hour) are given in Table 1.

Corresponding to the values in Table 1, the typical values of measured temperatures at eight hour intervals and at different thermocouple locations (TC3-TC11) are given in Table 2.

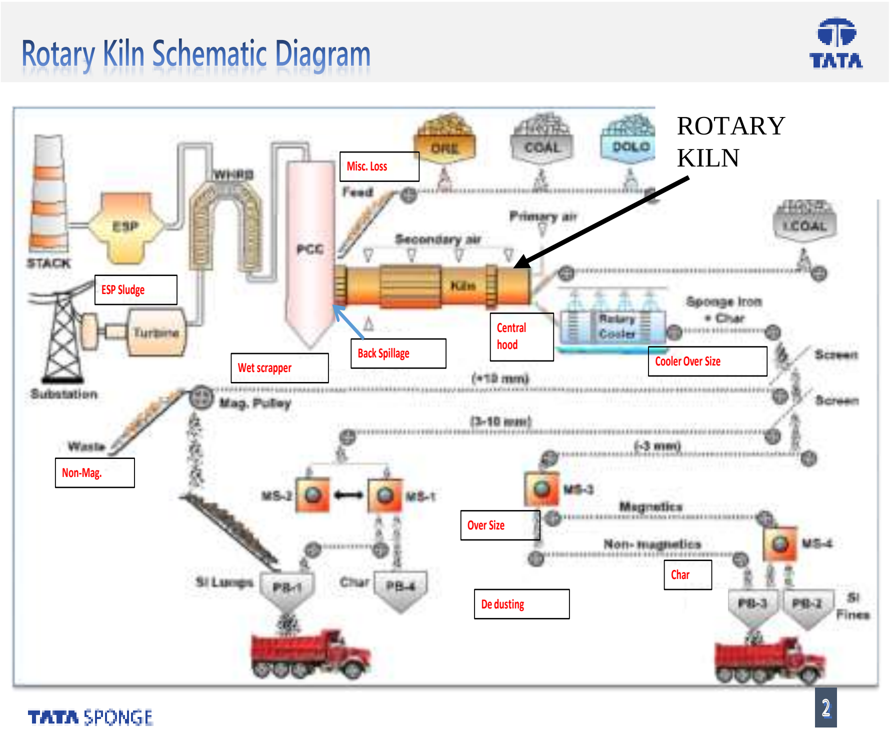

Fig.1. Schematic diagram of plant and the rotary kiln (see arrow mark) for production of sponge iron.

The campaign life of kiln may vary starting from 60 to 300 days, depending upon how it is operated. Operational control should be such that that product quality and production rate are maintained, subject to control of the growth of accretion inside the kiln. Accretions form due to sintering (or fusion) of charge materials at high temperature (800-1200ºC). The growth rate of accretion is predicted by a separate thermal model. The decision to change operating parameters is guided by growth rate of accretions at different locations inside the kiln. A typical growth profile of accretion at formed at TC7 and TC 10 (change in accretion thickness with number of days of operation) is shown in Figure 2; it can be seen that the accretion at TC7 has formed and broken because of the control strategy adopted through the models of present work; accretion at TC10 is also seen to increases and decreases in size. The effort is to restrict (or reduce) the growth of accretion while maintaining quality.

Table 1. Typical values of control parameters of rotary kiln.

PR.	PAB	ORE	RPM	FCIC	FCFC
7.8	11315	33.5	376.9	4.8	4.8
7.5	11479.7	35.4	388.2	5.4	4.6
8.3	10307.5	32.0	390.3	4.6	4.7
7.0	9395.2	30.5	347.0	4.3	4.7

SAB1	SAB2	SAB3	SAB4	SAB5	SAB6	SAB7	SAB8
6734.0	7280.0	6760.0	3744.0	4680.0	7670.0	7748.0	7540.0
6838.0	7774.0	6708.0	3822.0	4810.0	7540.0	7670.0	7618.0
6292.0	6578.0	5512.0	4238.0	3952.0	6240.0	6864.0	7176.0
5590.0	5850.0	5460.0	4238.0	4186.0	5902.0	7150.0	7540.0

Table 2. Typical values of temperatures, TC3 to TC11, along the length of kiln.

TC3	TC4	TC5	TC6	TC7	TC8	TC9	TC10	TC11
989.6	1029.3	940.4	819.7	947.2	997.1	1024.6	517.9	866.9
949.5	1010.5	1045.1	1088.5	1088.2	1027.3	1067.9	1115.3	972.3
1003.4	1014.5	1063.6	1035.5	1036.2	984.6	1032.2	833.3	907.6
964.9	1020.5	964.7	822.2	911.3	932.2	1019.7	536.7	868.5

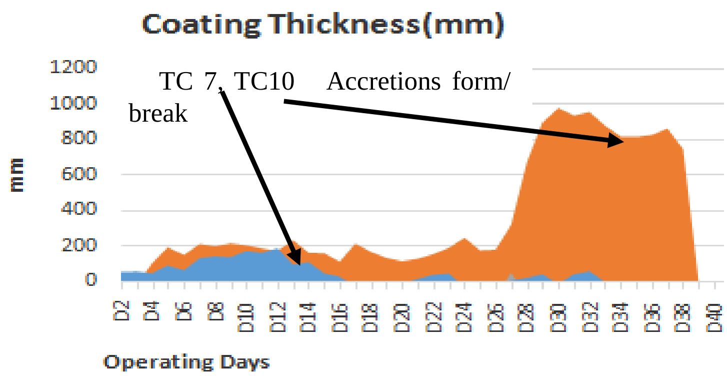

Fig. 2. Progress of formation of accretion at two different locations, TC7and TC10.

3. Results of models developed in present work

The results of different models for prediction of temperature (TC3-TC11), quality and pressure obtained and tested on actual plant data using ANN, multiple linear regression (MLR) and Extreme Learning Machine (ELM) are compared in Table 3. SEE means the standard error of estimate of parameter from independent variables, and Adj R^2 is adjusted correlation coefficient. The number of neurons finally selected for one middle layer, both in ANN and ELM, are given in the last two columns of Table 1, respectively. It can be seen that ELM out performs both ANN and MLR, both in terms of SEE, Adj R^2, except for the case of pressure where MLR gives the best results. An hourly analysis of pressure has revealed that fluctuations in pressure are actually chaotic with Lyapunov exponent greater than +2. For the present, MLR, by virtue of its better averaging effect through linearization, pressure prediction by MLR is better that by ELM and ELM under chaotic conditions. The chaotic pressure variations and its control will be discussed in a separate work.

The usual practice in plant is to employ MLR for determining different prediction equations to account for short term changes; it is always convenient to assume a linear behavior over short term periods. Typical results for TC6 temperature by using MLR is given in Fig. 3 and the results of quality prediction using MLR is given in Fig. 4. The parameters which are not contributing to prediction of a particular variable are dropped from regression equation on the basis of their relative importance. The typical equation for prediction of TC6 by MLR, for example, contains only four parameters, namely: air flow through Secondary Air Blower 1 (SAB1), SAB3 and primary air blower (PAB).

$$Tc6 = 0.018*SAB1 + 0.008*SAB2 + 0.008*SAB3 - 0.002*PAB \quad \textbf{(1)}$$

When ANN (artificial neural net) and ELM (extreme learning machine) are used for prediction, then all operational parameters are incorporated in the prediction set to account for their possible nonlinear contribution to the system and obtain better results of prediction.

Table3. Prediction results: TC is for thermocouple, Qual. is for quality, Pres. is for pressure

	SEE (±)			Adj R2			Number of Neurons in	
	ANN	MLR	ELM	ANN	MLR	ELM	ANN	ELM
TC3	11.06	14.16	6.62	0.66	0.42	0.88	11	85
TC4	9.71	10.23	8.06	0.29	0.19	0.43	10	55
TC5	21.92	40.26	12.39	0.82	0.37	0.94	11	85
TC6	35.33	40.15	9.16	0.85	0.81	0.99	12	85
TC7	21.06	24.58	8.15	0.78	0.70	0.97	11	85
TC8	41.16	70.95	27.25	0.82	0.45	0.92	13	85
TC9	23.53	28.93	13.37	0.51	0.25	0.84	10	80
TC10	83.96	58.64	12.51	0.85	0.94	0.90	11	80
TC11	19.52	15.27	7.97	0.80	0.87	0.97	12	80
Qual.	1.81	2.01	1.43	0.26	0.09	0.55	11	90
Pres.	0.56	0.33	0.62	0.59	0.72	0.55	13	85

Number of neurons in the middle layer have to be found out by trial and error, both in case of ELM and ANN. For example, for the worst prediction case of TC4 in Table 3, the effect of number of neurons in ELM is shown in Fig. 3; it can be seen that55 neurons are optimal for ELM in the case of TC4 where as in other cases 80-90 neurons are required for ELM.

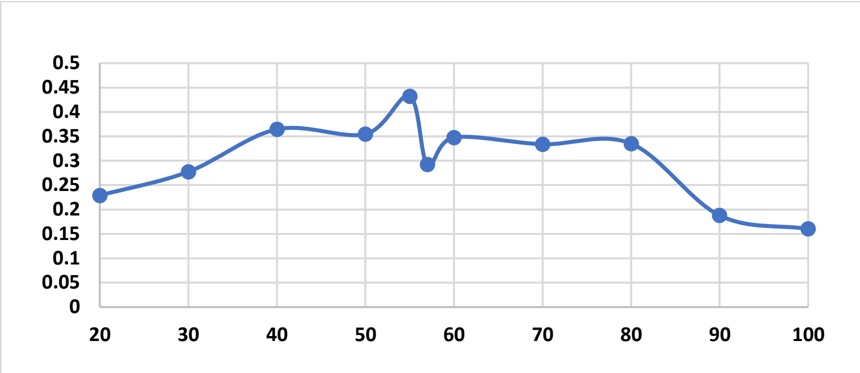

Fig. 3. Selection of optimal number of neurons in ELM.

It is observed during the shop floor application of models that the accuracy of prediction of all models decreases when accretion breaks down due to physical movement of charge. An advance indication of this can be obtained from chaos analysis (dynamic nonlinear chaotic changes through Lyapunov exponent) of pressure. In order to maintain the Lyapunov exponent in a desired window it is found that the pressure difference between inlet and outlet should be kept in the window of 4-6 mm. However, even then when the accretions break down, the pressure inside the kiln can change unpredictably and that is a very special feature and nature of coal fired rotary kilns. Nature always keeps the last card to play in it its own hand to respond to non-equilibrium conditions, similar to the phenomenon of formation and breaking of glaciers, except that the glaciers form when temperatures go down and break when the temperatures go up, whereas the accretions inside the kiln form and grow when temperatures go up. In contrast to glaciers accretions are always of a wave form on a cylindrical base due to constant and counter current movement of charge versus reducing gases inside the kiln.

If pressure is carefully measured and controlled then it is observed on the shop floor that accretions grow at a slower rate in a wave form (increasing in height gradually, see Fig. 2) and then eventually breaking down when the peak height reaches a particular level, depending upon the region of temperature. Accretions break when they are unable to resist the stresses (due to impact) of the rolling charge which is continuously striking at their base and on their side surfaces due to rotation of kiln. Besides pressure, therefore, the rotation rate of kiln is another important control parameter to be adjusted suitably, both for maintaining quality and also for restricting the accretion growth rate.

The feed rate of ore and coal are the next important parameters. The fines and ash content of coal enhance the accretion formation and must be regulated within a certain window for the process to be steady (for prediction purposes as well). All these features together make the control of rotary kiln a challenging task for the operator to produce and for the manufacturer to optimize the cost. Cost of coals with lower ash content and lower fines is progressively prohibitive to use in kiln.

The next step in improvement of control of kilns at TATA sponge would be automatic regulation of air blown through the secondary air blowers. Stable kiln operation directly determines stable power generation too because the waste gases from the kiln are used for steam generation which is then used for power generation. It is observed at TATA Sponge that after implementation of automatic pressure regulation the power generation has also stabilized proportionately, in spite of the fact that the total volume of secondary air blown has been reduced by at least 10 % compared to previous practices in which heat and mass transfer models alone were the guiding criteria.

Models developed and implemented in the present work have helped in reducing accretion growth rate and in quality control. Models developed by taking 4hr, 8hr, 16hr, 24hour and one month periods. Best results were obtained when the average response time of the kiln for iron oxide reduction and accretion control was taken as eight hours and the models are tuned on day-to-day basis accordingly. Pressure control is however done automatically (continuously, on-line) through PID controller.

4. Conclusions

Application of ELM, ANN, and MLR multiple based models along with dynamic pressure control is demonstrated for quality and accretion control in rotary kiln on shop floor. Quality is maintained and accretions are minimized. It is recommended to use ELM, in preference to ANN and MLR when data size is adequate, else MLR is to be used over short time intervals (10 days plus). For extrapolation into a new region over a short time period MLR is to be preferred. It is observed that the accretions grow and eventually break in a wave form. Pressure fluctuation is chaotic with an average Lyapunov exponent of approximately +2. For a given raw material input quality (ash in coal + its fine size fraction, and reducibility and Fe content of ore) the important control parameters are pressure, rotation speed of kiln, feed rate of ore and coal, and ratio of feed coal to injection coal, in that order. As a result of pressure regulation and better process control, the volume of secondary air requirement has been reduced by 10%. As an added benefit, the power generation has also been stabilized proportionately. Since the growth rate of accretions has been reduced it is expected that the campaign life of kiln will increase. The trials are continuing for further improvements. The two critical response times lying on two extremes of control, i.e. few seconds for pressure control extending to 8 hour duration for iron oxide reduction and accretion control in kiln, make the control of rotary kiln operation special in its own way.

Acknowledgement

The authors (SC, PC, BD) from IIT Bhubaneswar are very thankful to the management of TATA Sponge Iron Limited (TSIL) for giving an opportunity to work with

TSIL engineers and learn from them the practical aspects of kiln operation. Perhaps it will serve as an encouraging example to showcase how an industry takes a step forward to promote joint industry-academia efforts.

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