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Prediction of Hot Metal Temperature Using Multivariate Data Science Approach for Blast Furnace Iron Making Process

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Abstract

This paper presents the determination of health status of blast furnace based on the principle component analysis and multivariate analysis. The health status of Blast Furnace (BF) represented in terms of 'hot metal temperature' is an important parameter to regulate the smooth operation coupled with continued production of hot metal to avoid the major danger events to happen. The health index also indicates the performance of BF at early stage so that the operator can take appropriate actions to avoid deterioration in the blast furnace in prior. The health status of blast furnace indicates the stability or instability condition of BF, which might occur during the production process and is used to recognize the fault. The principle component analysis techniques has been widely used in various industrial fields due to its various advantages such as, it does not require the knowledge of the process and faults. In this paper, based on past dataset collected from blast furnace, principle component technique is applied using weka; a software application; that employs pre-processing, clustering, classification and selective attribute modules for development of the health status of BF. The health status has been tested with varying process data and is found to be useful in identification of process abnormality in BF.

Introduction

The Blast Furnace (BF) is a complex process and requires stability for the smooth operation and consistency in hot metal productivity. The BF being a continuous reactor (Figure 1) should be stable so that the fuel demand is reduced and hot metal production can be maximized. The instability in BF leads to extra fuel demand and reduces the production rate. The stability of BF depends on various factors and the determination of BF stability would facilitate BF operator to maintain the furnace in healthy condition. The hot metal temperature represents an important key performance indicator in blast furnace operation. In BF operational practice, when the casting takes place hot metal drawn from the taphole falls into the respective trough, where using an optical pyrometer or thermocouple, the hot metal temperature is measured. The hot metal temperature indicates the thermal level of BF. Too high hot metal temperature represents furnace heating up, while a lower value represents furnace chilling down. The hot metal temperature is usually measured 3 times in a cast viz., immediately on opening the cast, in the middle of cast and towards the end of cast. It is envisaged that the hot metal temperature increases with the progress of the cast. When the cast is closed, the hot metal resides inside the hearth. During its residence inside the hearth, the hot metal remains in contact with coke present in dead man zone and the hearth refractory, wherein the gradual thermal loss takes place. It is therefore, the longer residence time of hot metal inside the hearth reduces the hot metal temperature. Therefore, the hot metal temperature measured immediately on opening the cast is comparatively lesser. While, the hot metal temperature measured towards the end of cast is usually highest in-cast; this is because towards the end of cast, the hearth is already drained with the accumulated hot metal and the freshly prepared hot metal dribbling from the dripping zone are tapped out from the furnace immediately, which does not get enough time for its residence inside the hearth. Consequently, the hot metal temperature measured towards the end of cast is higher and therefore represents the current thermal state of BF.

Attempts are made in the determination of thermal performance of the BF through development of mathematical model [1-3]. These models represent the thermal indicators such as % Si, Hot Metal Temperature (HMT) and can also predict the thermal tendency of BF in advance. Moreover, with the availability of plant data, the data-based approach of process modelling has been emerging as an important method to forecast the thermal level in BF. Several attempts are made to develop data-based models that numerically solves the plant process problems that can describe the process alternatively. Further, attempts are made by Martin et al. using fuzzy logic tools to predict the HMT in BF [4]. Jimenez et al. has reported the prediction of HMT and its evolution based on neural networks based model using the blast variables as an input to the model [5]. This paper presents a simplified mathematical model developed based on the multivariate analysis for predicting the hot metal temperature in blast furnace. In the present work, data from the practical BF is considered and based on the historical data of BF, the development of model is carried out.

Principal component analysis applied to blast furnace process

The principal component analysis is a statistical approach used to reduce the dimensionality of the parameters. In the present work, principal component analysis is used because the BF consists of various controllable and uncontrollable parameters. It is comparatively easier to develop insight about the process parameters and establish correlation among them. However, raw materials that are fed into the BF are uncontrollable. Since raw materials play an important role in the BF operation, it become necessary to understand the effect of raw materials on the BF health condition. In the BF process the raw materials are sampled intermittently, and there is no online sampling of raw materials. Therefore, the required means to establish the correlation between raw material quality with the BF health index is not possible. In the present work, therefore instead of mathematical approach, the data based approach is adopted to model the abnormality in BF.

Attempts are made to make use of principal component analysis for developing principal components for identifying the occurrence of the abnormality such as hanging and slipping in furnace, wherein the points lying inside the ellipse represents the healthy condition of furnace [6-11]. British Steel has applied the principle of principal component analysis for detecting

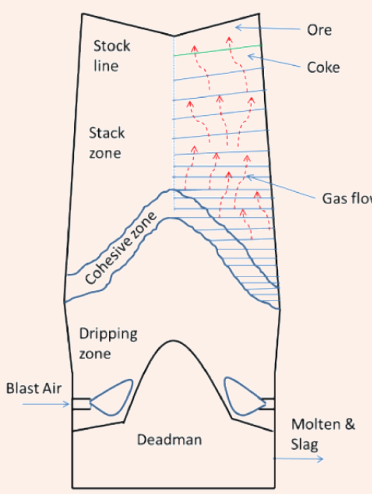

Figure 1: The Blast Furnace process showing various processes [12].

the instability in BF using stock line measurements for determining the slipping and channelling occurring inside the furnace [6]. It has been further demonstrated that the principal component migrates from main cluster, which is the stable region and moves into the unstable region. This representation has facilitated the BF operators to proactively reduce the blast volume. Further, an index is deduced to provide the information about the furnace behaviour. The burden descent rate, top gas temperature, gas utilization, differential pressures and gas permeability resistance are the various parameters used in principal component analysis, for developing the principal components and a multivariate statistical control chart is formulated. Channelling is a non-homogenous condition of the burden distribution where ascending gases tries to preferentially flow, resulting in changes in the gas flow pattern in top gas and subsequently affects the burden movement down the stock line. It is because of these reasons that process parameters are suitably selected for identification of channelling and slips in BF. Gamero et al. has attempted to predict the aerodynamic instability in BF using stack pressures. The principal component analysis has been applied to detect the instability in BF and the system gives various alerts like reducing of the blast volume to minimise the instability occurring in BF [7].

The above research on principal component analysis has been an effective approach for detecting the slipping and channelling in BF. These work is further extended by Zhou et al. to cater with the non-normal process distribution and the time-varying nature in the measurement data by applying the static convex hull-based principal component analysis algorithm [8]. The various parameters used are blowing parameters, pressure measurements, top gas measurement data, permeability indices of BF and along the height of the BF using which channelling, slipping and hanging abnormalities in BF are detected [9]. The determination of the blast furnace health index is very challenging task, as if it is totally based on data analysis which is an iterative process. In the BF operation, there are numerous variables therefore the difficulty in analysing the process variables during the abnormal furnace condition becomes time-taking. Therefore, there is a need to deduce an index that can best represent the overall process variable. Principle component analysis has been widely used in various industrial fields due to its advantages. The principle components analysis is a data reduction technique without losing the information of data. The principle component analysis is used to calculate the health index of BF and identify

Table 2: Input variables, Units, Range of Data and their coefficient with Hot Metal Temperature.

Parameter	Unit	Minimum	Maximum	Mean	Standard Deviation	Coefficient
Constant						1030.149
STR	%	76.9	100	94.6	4.9	-0.027
TUY_VEL	m/s	177.4	192.2	186.3	2.7	-0.272
HBT	°C	1166.6	1211.8	1186.3	7.1	-0.053
CBV	KNm^3/h	181.9	220	196.1	5.1	0.21
Coke_Rate	Kg/thm	302	330	314.1	6.8	0.11
Raft	°C	2004	2291.1	2164.2	47.2	0.027
ETA_CO	%	47.6	51.4	49.9	0.6	3.458
O2_ENR	%	6.2	8.8	8.1	0.4	1.275
Blast_Moist	g/Nm^3	15	27	15.1	0.7	0.095
BGV	KNm^3/h	275.2	319.2	299.1	8.8	0.162
MID_K	Ratio	0.6	1.3	0.9	0.1	-1.265
B_1	°C	44.4	61.8	51.5	2.8	-0.963
B_2	°C	46.7	77.2	54.9	4.6	-0.388
S_1	°C	47.9	84.5	57.8	6.5	0.287
S_2	°C	47	84.2	56.1	4.6	-0.19
S_3	°C	49.9	68.6	58.2	3.1	1.039
S_4	°C	53.5	73.1	61.3	3.5	-0.47
R_1	°C	46.2	103.5	66.7	9	0.063
R_2	°C	52.2	102.6	76.1	9.9	0.435
R_3	°C	45	82.2	64.8	7.3	-0.52
Previous HMT	°C	1450	1532	1496	15	0.171
Time_Diff	Min	30	300	166.1	45.6	-0.028
Coal_Rate	Kg/thm	190	226	208.3	7.7	-0.169
Si	%	0.22	1.34	0.72	0.18	41.193

Table 1: Correlation Matrix of process Parameters.

Variables	STR	TUY_VEL	HBT	CBV	PCI	Coke	ETA_CO	O_2_EN	BGV	MID_K	B_1	B_2	S_1	S_2	S_3	S_4	R_1	R_2	R_3	HMT
STR	1																			
TUY_VEL	0.311	1																		
HBT	0.086	0.193	1																	
CBV	0.129	0.482	-0.027	1																
PCI	0.236	0.421	0.24	0.119	1															
Coke	-0.044	-0.149	-0.125	-0.02	-0.688	1														
ETA_CO	-0.037	-0.209	-0.03	-0.068	0.272	-0.582	1													
O2_EN	0.19	0.417	0.148	-0.081	0.589	-0.266	-0.093	1												
BGV	-0.215	-0.178	0.212	-0.155	-0.351	-0.092	-0.08	-0.371	1											
MID_K	-0.226	-0.443	0.038	-0.328	-0.382	0.167	0.037	-0.389	0.341	1										
B_1	-0.059	-0.068	0.058	-0.081	-0.129	0.174	-0.194	-0.092	0.025	0.192	1									
B_2	-0.088	-0.32	-0.087	-0.124	-0.5	0.294	-0.203	-0.456	0.322	0.502	0.348	1								
S_1	-0.185	-0.487	0.02	-0.279	-0.575	0.253	-0.095	-0.513	0.512	0.641	0.392	0.737	1							
S_2	-0.046	-0.426	-0.051	-0.19	-0.513	0.281	-0.098	-0.46	0.396	0.392	0.286	0.648	0.739	1						
S_3	-0.038	-0.44	0.012	-0.23	-0.477	0.308	-0.093	-0.384	0.304	0.416	0.331	0.613	0.703	0.904	1					
S_4	-0.011	-0.021	0.006	0.004	-0.228	0.343	-0.301	-0.249	0.022	0.404	0.336	0.537	0.449	0.194	0.238	1				
R_1	0.04	0.322	-0.04	0.162	0.231	0.073	-0.261	0.147	-0.288	-0.013	0.043	-0.064	-0.212	-0.513	-0.463	0.605	1			
R_2	0.065	0.266	-0.112	0.194	0.093	0.224	-0.274	-0.036	-0.295	0.012	0.061	0.072	-0.173	-0.297	-0.25	0.624	0.893	1		
R_3	0	0.199	-0.111	0.153	0.063	0.212	-0.23	-0.068	-0.274	0.078	0.1	0.076	-0.116	-0.299	-0.237	0.616	0.89	0.974	1	
HMT	0.19	0.226	0.039	0.163	0.028	-0.062	-0.062	0.22	-0.055	-0.032	-0.141	-0.002	-0.192	-0.051	0.016	-0.024	0.004	0.049	-0.006	1

the stability and/or instability condition of BF through identification of fault during the BF operation.

Results and Discussion

(Figure 2) shows the input parameters used in the prediction of hot metal temperature. It can be seen from the figure that the process variables bear variability in the data. The variability in process leads to the variability in the hot metal quality. However, with the inconsistent quality of blast furnace material and variability in process, the blast furnace always thrives for the quality production of hot metal. Therefore, it becomes important to predict the hot metal quality in advance so that operational nuances occurring inside the blast furnace can be forecasted in prior and necessary actions can be taken either to eliminate the abnormality of reduced it significantly.

(Table 1) shows the correlation matrix among parameters. Using a set of 24 parameters derived based on the process knowledge, data is filtered, cleansed and trained to generate coefficients for predicting the hot metal temperature. This is carried out in

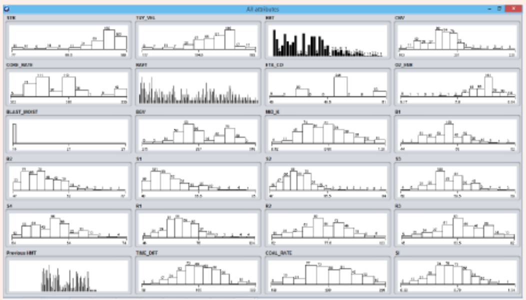

Figure 2: Input Parameters and Histogram showing process variability.

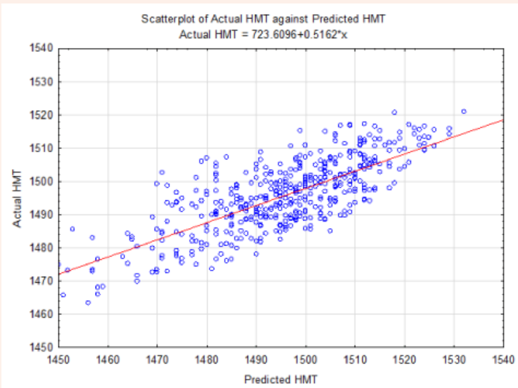

Figure 3: Actual HMT vs Predicted HMT.

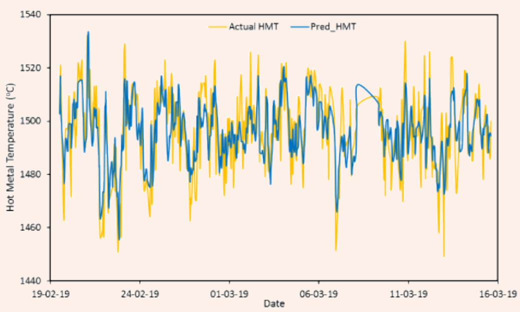

Figure 4: Actual HMT vs Predicted HMT.

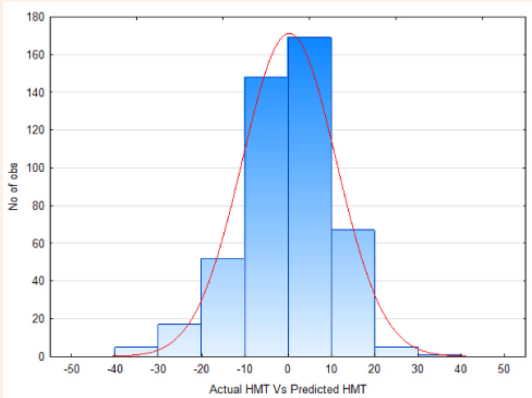

Figure 5: Error in Actual HMT vs Predicted HMT.

Statistica server version 13. The results give the coefficients that can be seen in the below (Table 2). It can be seen from (Table 2) that hot metal Si shows higher value of coefficient with predicted hot metal temperature, which means that Si increases simultaneously with predicted hot metal. While developing the analysis, it was found that heat loss from circuit #3 was showing relationship but its correlation coefficient was significantly lesser and even on ignoring the variable, there was no effect on the hot metal temperature, therefore, it was removed from the analysis. Further, multivariate analysis is made on the data filtered after the application of principal component analysis. The hot metal temperature which is represented as an important health condition of the blast furnace is predicted based on the historical data. (Figure 3) shows the actual vs predicted hot metal temperature. (Figure 4) shows the trend of the actual hot metal temperature as compared to the predicted hot metal temperature. It can be further seen from (Figure 5) that an accuracy of ±10°C is found in the almost 90% of the predicted hot metal temperature compared to actual hot metal temperature measured from the dip sampler analysis. Around 10% predicted hot metal temperature shows prediction with an error of ±20°C.

Therefore, it is evident that the predicted hot metal temperature can make an approximate estimate of actual hot metal temperature. The variation in hot metal temperature is primarily caused due to the variation in the raw material chemistry [13-14] and because of the process conditions [15-21]. It is recommended that if the predicted hot metal temperature is significantly increasing than it can be informed to the respective area owner through system [22].

Conclusion

Following conclusions can be made based on the present work:

i. The principal components analysis has been successfully applied for the BF process data for reducing the number of parameters affecting the BF health condition.

ii. Further, multivariate analysis is made on the data filtered after the application of principal component analysis. The hot metal temperature which is represented as an important health condition of the BF is predicted based on the historical data.

iii. An accuracy of ±10°C is found in the almost 90% of the predicted hot metal temperature compared to actual hot metal temperature measured from the dip sampler analysis.

iv. Around 10% predicted hot metal temperature shows prediction with an error of ±20°C.

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Conflict of Interest

No conflict of interest from authors.

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