Diagnosis and Control of Hot Metal Quality of Blast Furnace in an Integrated Steel Plant

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Abstract- The quality of products and processes has proven to be crucial for companies to compete in the market. Statistical process control enables them to foresee problems in the process, thereby ensuring the quality of manufactured items. This chapter aims to present a proposal for monitoring a hot metal production process in an integrated steel plant with the help control charts. This research arose from the need to monitor smelting process in a blast furnace in which hot metal is produced in the integrated steel plant. For monitoring this process, Shewhart X -R control charts are used for nine quality parameters of hot metal quality, analyzing them separately. To complement, a multivariate Hotelling's T2 chart is used to monitor these nine measurements simultaneously. The two approaches are compared in terms of performance and usage aspects. Though, the Stewart control chart is easier to use and simpler to interpret by operators these charts may fail to interpret the out of control instances when there is moderate or strong correlation among the variables. Hence in this study, multivariate control chart (Hotelling's T2) is adopted to monitor the smelting process of blast furnace. Also, multi-variate statistical process control diagnosis through principal component analysis is presented to help the management to react correctly when they encounter the out-of-control measurement, and lower the defect product rate.

Key words: Shewhart X -R control charts, Hotelling's T2 chart, Principal component analysis

I. INTRODUCTION

Since the pioneering work of Shewhart in 1931, control charts have been successfully used to monitor process performance over time. They have been a foundation for maintaining and achieving new unprecedented levels of quality. However, these are generally classified as univariate charts that can only be used to monitor a single characteristic of a stationary process. Advancements in technology and increased customer expectations have raised the need to monitor correlated variables simultaneously. This requires the utilization of multivariate control charts, enabling engineers and manufacturers to monitor the stability of their systems. Under these conditions, achieving a state of statistical control requires a higher level of knowledge regarding the process variables, the level of correlation among them, and the accuracy by which they can be controlled.

II. LITERATURE SURVEY

Nurudeen et al. (2019) [1] presented a multivariate homogeneously weighted moving average (MHWMA) control chart for monitoring a process mean vector and illustrated the proposed chart with a numerical example. In the study, the authors provided the design procedure and compare the average run length (ARL) performance of the proposed chart with multivariate Chi-square, multivariate EWMA, and multivariate cumulative sum control charts.

Henning et al. (2014) [2] used Shewhart X -S control for three measurements performed in sections of a cylinder, analyzing them separately and also a multivariate Hotelling's T2 chart is used to monitor these three measurements simultaneously. The two approaches are compared in terms of performance and usage aspects. Similar results are obtained and these results enabled the company to know process stability, facilitating decision-making on actions taken for improvement.

Custodio Alves et al. (2013) [3] investigated significant differences in sensitivity between the use of Multivariate Cumulative Sum (MCUSUM), Multivariate Exponentially Weighted Average (MEWMA) control charts and Hotelling T2 charts to detect small changes through an industrial application of the mean vector of a process of machining process. The results obtained in this study suggest that the MCUSUM chart is an excellent statistical tool for the monitoring of a machining process with multiple quality characteristics

Jaka Nugraha et al. (2017) [4] applied multivariate Hotteling T2 Individual control chart for wastewater treatment using wastewater treatment data from PT. ICBP, east Java branch. The authors found that Multivariate control chart for Biological Oxygen Demand(BOD)- Chemical Oxygen Demand (COD) and BOD- Total suspended Solid (TSS) are each one subgroup that are outside the control limits.

Salah Haridy and Zhang Wu (2013) [5] presented process monitoring and adjustment methodologies for addressing dynamic behavior problems of cold rolling process using univariate and multivariate control charts. The authors suggested that when the multivariate control chart detects a change, then the univariate control charts will be helpful in determining the characteristic, which caused this change.

Sutirman, et al. (2015) [6] investigated method of multivariate controls charts and univariate control charts to identify a significant for monitoring and controlling the process by considering sugar production process. In the study, the authors found that HotellingT2 is capable to detect the out of control points in the sugar production process.

Ketllin Z. da Conceição et al. (2018) [7] determined the water quality index of the Passaúna and Piraquara rivers and applied the control charts of individual Shewhart, EWMA and CUSUM. In the study, the authors demonstrated that they are fast and efficient techniques for the evaluation of water quality control,

Onwuka, Gerald. I. (2012) [8] applied Principal Component Analysis and Hotelling's T2 to a pipes industry using measurable characteristics (diameter, length and circumference) to monitor the in-control condition in pipes production.

Alessandro Corsinia et al. (2015) [9] addressed CUSUM control chart (univariate) based on the standard deviation and T2 control chart for the monitoring of compressed air line in term of operational and energy variables. In conclusion, the authors felt that besides the improvements obtained in the industrial processes energy analysis field, still, none of these models appears to be completely adequate.

Hamed. M.S. (2017) [10] developed Hotelling's T2 quality control chart to determine whether or not the process mean vector for two or more variables of fertilizers factory. In the study, it was observed that in the evaporation and prilling stage, test results of Hotelling T2 chart indicates that the out-of-control percentage by 2.87%.

M. A. Sharaf El-Din et al. (2006) [11] studied the application of univariate and multivariate control charts in the field of steel industry. Performance analysis for each charting method is studied using the Average Run Length (ARL). A comparison of the univariate out-of-control signals with the multivariate out-of-control signals is also made to illustrate the efficiency of the Hotelling's T2 statistic

Shivi Bhasin (2016) [12] made a study for assessment of water quality of Kshipra river by use of control chart by considering quality parameters like dissolved oxygen (DO), chemical oxygen demand (COD), biological oxygen demand (BOD), total coliform (TC), fecal coliform (FC), turbidity, transparency, total alkalinity, total hardness, chloride, calcium. Results of the present investigation showed that water quality of the river is more deteriorated during summer followed by monsoon and winter season.

Chandra and Menezes (2001) [13] implemented multivariate techniques to marketing research in respect of National Tourism Organizations (NTO) to identify key components of the marketing strategy of NTOs.

Tsung and Apley (2001) [14] provided dynamic T2 chart that improves the detection of assignable causes in feedback-controlled processes.

Tsung and Apley (2004) [15] adopted autoregressive T2 control chart for statistical process for control and monitoring of auto-correlated processes

Marina Vives-Mestres et al. (2017) [16] proposed a multivariate control chart for individual compositional observations based on the T2 statistic and compared with the typical one in terms of average run length using a numerical example. In the study, the results are more consistent with compositional data nature

Kourti (2005) [17] reviewed the developments in multivariate statistical process control (MSPC) and its application for fault detection and isolation (FDI) in industrial processes. The author elaborated the methodology in the industrial environment.

Scordaki and Psarakis (2005) [18] considered that application of statistical process control techniques for commercial process. In their study the authors developed the application of control charting techniques in the sales and logistic departments.

Panyaping (2006) [19] monitored wastewater generation and production conditions in the manufacture of textile products of Textile Industry in Samutprakarn Province by the application of the multivariate analysis technique as a management tool.

Bersimis et al. (2007) [20] reviewed multivariate extensions for all kinds of univariate control charts, such as multivariate Shewart type control charts, multivariate CUSUM control charts and multivariate EWMA control charts.

Zou and Qiu (2009) [21] developed LASSO-based multivariate test statistic, which integrated into the multivariate EWMA charting scheme for protection against various shift levels, shift directions. The authors opined that the statistic provides an effective tool for multivariate SPC applications.

Fábio Orssatto et al. (2014) [22] used statistical methods of quality control to evaluate the performance of a sewage treatment station located in Cascavel city using quality parameters (hydrogenionic potential, settleable solids, total suspended solids, chemical oxygen demand and biochemical oxygen demand) in five days. Statistical analysis was performed through Shewhart control charts and process capability ratio

Md. Belal Hossain and Mohammad Shahed Masud (2016) [23] studied the performance of Shewhart $\overline{X}$ control chart and Hotelling T2 control chart for correlated bivariate and multivariate with three variables of quality characteristics to control the process mean using simulation study. In the study, the authors identified that Hotelling T2 control chart performs better than Shewhart $\overline{X}$ control chart

Mary Waterhouse et al. (2010) [24] considered the implementation and performance of the T2 multivariate exponentially weighted moving average (MEWMA) and multivariate cumulative sum (MCUSUM) charts in light of the challenges faced in clinical settings to handle incomplete records and non-normality of data.

III. T2 CONTROL CHART METHODOLOGY

To monitor the process, the methodology of T2 generalized variance control chart is used with the following procedure

Step-1: Investigate and identify the process variables

The practitioners should know what input variables need to be stable in order to achieve stable output, and then those variables are suitable to be monitored. In this study, the critical variable of the process are identified by regression analysis. As regression attempts to describe the dependence of a variable on one (or more) explanatory variables, it implicitly assumes that there is a one-way causal effect from the explanatory variable(s) to the response variable, regardless of whether the path of effect is direct or indirect.

Generally, not all quality attributes and process variables are equally important. Some of them may be very important (critical) for quality of the product performance and some of them may be less important. The practitioners should know what input variables need to be stable in order to achieve stable output, and then these variables are to be monitored appropriately. Regression Analysis may identify the critical process variables. The Regression Analysis tool performs linear regression analysis by using the “least squares” method to fit a line through a set of observations. It can analyze how a single dependent variable is affected by the values of one or more independent variables. Regression Analysis is a technique for estimating the relationships among variables in process and to predict a dependent variable(s) from a number of input variables.

Step-2: Examine the dependency between these variables

It is also necessary to examine the dependency between these variables. Coefficient of correlation between variables is a good indicator to know the extent of relation among the variables. Minitab, statistical software is used to generate correlations among the process variables from the data.

Step-3: Examine autocorrelation

Autocorrelation or seasonal dependency is a measure of the dependence between data points that are collected over time. If the autocorrelation is moderate or high, it can lead to incorrect test results. Auto correlated data exhibit positive autocorrelation, which can reduce the within-subgroup variation and lead to a higher false alarm rate (StatSoft, 2013).

Correlograms are autocorrelation plots that can show the presence of autocorrelation. In most software packages, autocorrelation functions are presented. It tells the amount of autocorrelation between a variable and a lag that is not explained by correlations at all lower-order- lags. In the graph of an ACF function examine the spikes at each lag to determine whether they are significant. A significant spike will extend beyond the significance limits, which indicates that the correlation for that lag doesn't equal zero.

Before implementing T2 Control Chart methodology it is necessary to check for autocorrelation. As a computational resource for the monitoring of data, the normality and autocorrelation analysis was done using Minitab 18 software package.

Step-4: Building the Univariate Charts

Schewart Quality Control Charts are developed for the data collected on various quality characteristics. Both Xbar and R Charts are built for the quality characteristics using the equations given in Table-5.1. Minitab is employed for drawing the control charts for each quality characteristic. The process is in control as all the points are within control limits and hence these limits are standardized for the future production and subsequent on line quality control. All samples that exceeded the limits for at least one of the quality characteristics were excluded from further analysing/processing.

Step-5: Building T2 Control Chart for phase I

The Univariate Schewart Control Charts hitherto made are voluminous if the number of quality characteristics is increasing. The multivariate quality control chart is handy in such conditions owing to the advantage of cost reduction and high sensitivity against variation in the process. The upper control limits and lower control limit of the T2 chart are computed by using Minitab 18.

Step-6: Building T2 Control Chart for phase II

Control process of 2nd Phase process starts. It is determined whether new observation vectors, which are selected from the process randomly, are under control or not by basing on main parameters estimated from reference data set in the 1st Phase. In this phase T2 Control Chart limits are determined based on the mean and variance of reference data set using Minitab 18. When T2 values of new examined observation vectors exceed UCL, one can infer that observations are not in conformity with the main data set.

3.1 Principal component analysis

Principal component analysis (PCA) is a classical data analysis technique that finds linear transformations of data that retain the maximal amount of variance. PCA is a technique for taking high-dimensional data, and using the dependencies between the variables to represent it in a more tractable, lower-dimensional form, without losing information. While the Process Variables may be correlated with one another, the Principal Components are defined such that they are orthogonal, or independent of one another, which is necessary for the analysis (Mardiaet al. 1979, Jackson 1991, MacGregor, et al., 1994). PCA seeks the linear combinations of the original variables such that the derived variables capture maximal variance. PCA can be done via the singular value decomposition of the data matrix. Contribution Charts are available for determining the contributions of the process variables to either the Principal Component (Score Contributions) or the Squared Prediction Error (Error Contributions) for a given sample. This is particularly useful for determining the Process Variable that is responsible for process shifts. Marengo et al. (2003) incorporated principal components analysis in multivariate control charts to monitoring an industrial process.

PCA has been used in gene expression data analysis (Misraet al. 2002).Hastie et al.(2000) propose the so-called Gene Shaving techniques using PCA to cluster high variable and coherent genes in microarray data.

There is a limited research in monitoring of complex processes in continuous process industries through Multivariate statistical process control. Hence in this study, a real case from a steel-making industry is considered and multivariate statistical process control is adopted to identify the correlation between multiple variables and monitoring of these variables. PCA technique is also adopted to analyze the problematic variables. PCA is implemented using Minitab 18. The following results are necessary for diagnosis of quality characteristics.

3.2 Eigen values

The eigenvalues measure the amount of variation retained by each principal component. Eigenvalues are large for the first PCs and small for the subsequent PCs. That is, the first PCs correspond to the directions with the maximum amount of variation in the data set. One can examine the eigenvalues to determine the number of principal components to be considered. An eigenvalue > 1 indicates that principal components account for more variance than accounted by one of the original variables in standardized data.

3.3 Principal components

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables (entities each of which takes on various numerical values) into a set of values of linearly uncorrelated variables called principal components. The principal components are the linear combinations of the original variables that account for the variance in the data. The maximum number of components extracted always equals the number of variables. To interpret each principal component, examine the magnitude and direction of the coefficients for the original variables. The larger the absolute value of the coefficient, the more important the corresponding variable is in calculating the component.

3.4 Principal component scores

Scores are linear combinations of the data that are determined by the coefficients for each principal component. To obtain the score for an observation, substitute its values in the linear equation for the principal component. Minitab 18 stores the component scores of each observation.

3.5 Contribution

The eigen value associated to a component is equal to the sum of squared factor scores of the component. Therefore, the importance of an observation for a component can be obtained by the ratio of the squared factor score of this observation by the eigenvalue associated with that component. The ratio is called as the contribution of the observation ‘i’ to the principal component ‘l’. Formally the contribution of observation is denoted by ctri,l is obtained from the following relation.

Ctri,l = f2il / Σ f2il

where fil is component score of ‘ith’ observation to the ‘ lth’ component.

This paper studies the application of multivariate statistical process control charts to monitor hot metal production in blast furnace with the help of T2 diagnosis. Further Principal Component Analysis (PCA) is applied to find out the contribution of critical process variables. A case study of hot metal production in a blast furnace of integrated steel plant is considered for multi variate process control to monitor and diagnosis of the smelting process.

IV. CASE STUDY

A case study of an integrated steel plant, in the area of production of hot metal in a Blast Furnace is presented to identify, evaluate, improve and control of defectives in hot metal production. The goal is to find systematic and appropriate approach to achieve improvement in quality of hot metal by the application multivariate control charts and principal component analysis. A set of data containing 200 observations is collected for fifty days. In each day 4 tapping times are randomly selected and the data on ten quality characteristics (Hot metal Yield (Y), %Si, %S, %Mn, %CO2 , %CO, SOx, NOx and PM) as discussed earlier regarding hot metal production is collected for multivariate process control and diagnosis of critical characteristics for monitoring of smelting process.

4.1 Results and discussion

4.1.1 Critical process variables

Regression Analysis using Minitab 18 is adopted to identify the critical process variables. Overall hot metal quality as discussed in earlier is considered as dependent variable and ten process variables are considered as independent variables. The results are presented below.

Regression analysis outputs: Coefficients summary is presented in Table-1. From the results it is observed that the predictor variables of Yield, %S, %P, %Mn, CO2, CO and PM are significant since their p-values are <=0.05. However, the p-value for %Si (0.603), SOx (0.115) and NOx (0.482) are greater than the common alpha level of 0.05, which indicates that it is not statistically significant.

Table-1: Coefficients summary

Term	Coef	SE Coef	T-Value	P-Value
Constant	11.2	13.1	0.86	0.39
Yield	0.555	0.275	2.02	0.045
Si(%)	–9	17.2	–0.52	0.603
S(%)	–162.2	12.2	–13.27	0
P(%)	–220.3	18.2	–12.13	0
Mn(%)	294.1	11.5	25.57	0
CO2	0.1852	0.0447	4.15	0
SOx	–0.1256	0.0793	–1.58	0.115
CO	–0.00138	0.000177	–7.8	0
NOx	–0.00022	0.000309	–0.7	0.482
PM	0.00398	0.00148	2.69	0.008

Model summary is presented in Table-2.

Table-2: Model summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.02964	99.86%	99.85%	99.73%

From R-squared value (99.86%), it is observed that the data closely fitted to the regression since. It is also known as the coefficient of determination. Theoretically, the model could explain 99.86% of the variance. The adjusted R-squared (99.85%) is a modified version of R-squared that has been adjusted for the number of predictors in the model. The predicted R-squared (99.73%) indicates how well a regression model predicts responses for new observations. Closeness of the values indicates goodness of fit of regression model. Hence in this study, seven variables namely: Yield, %S, %P, %Mn, CO2, CO and PM are considered for further analysis.

4.1.2 Correlation between the variables

It is also necessary to examine the dependency between these variables. Coefficient of correlation between variables is a good indicator to know the extent of relation among the variables. Minitab, statistical software is used to generate correlations among the process variables from the data. Table-3 shows the correlation among the process variables generated from the data.

Table-3: Correlations

Variable	Yield	S(%)	P(%)	Mn(%)	CO2	CO
S(%)	–0.997 (0.00)					
P(%)	–0.998 (0.00)	0.994 (0.00)				
Mn(%)	–0.978 (0.00)	0.984 (0.00)	0.971 (0.00)			
CO2	–0.991 (0.00)	0.996 (0.00)	0.988 (0.00)	0.993 (0.00)		
CO	–0.082 (0.25)	0.071 (0..32)	0.088 (0.22)	0.065 (0.36)	0.07 (0.32)	
PM	0.262 (0.00)	–0.269 (0.00)	–0.252 (0.00)	–0.295 (0.00)	–0.28 (0.00)	0.072 (0.31)

From correlation table it is observed that there is strong correlations among Yield, %S, %P, %Mn, CO2 and PM and they are significant since the p-values shown in brackets are <=0.05. Hence these variables are considered for further analysis. Correlations of these variables with CO is insignificant as the p-values are >0.05 and is not considered.

4.1.3 Normality test

The normality test was conducted using Minitab18 and the graphs are shown in Figure-1 below.

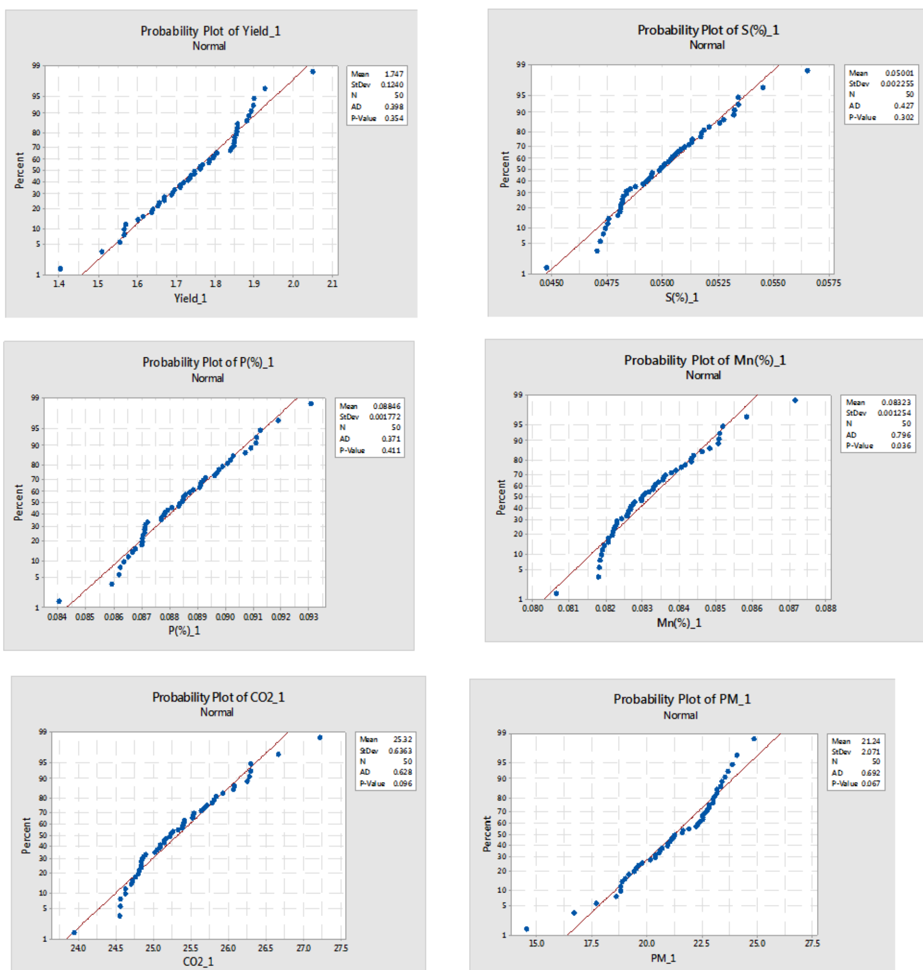

Figure-1: Normality test

Normality test is performed using Minitab 18. From the test it is observed that except variable '%Mn' all the variables follows normal distribution since the p-value is greater than 0.05, rejecting the null hypothesis. Thus the inference is "Data follows a normal distribution".

4.1.4 Auto correlation

Auto correlation function graph is drawn using Minitab 18 and the graphs are shown Figure-2 below.

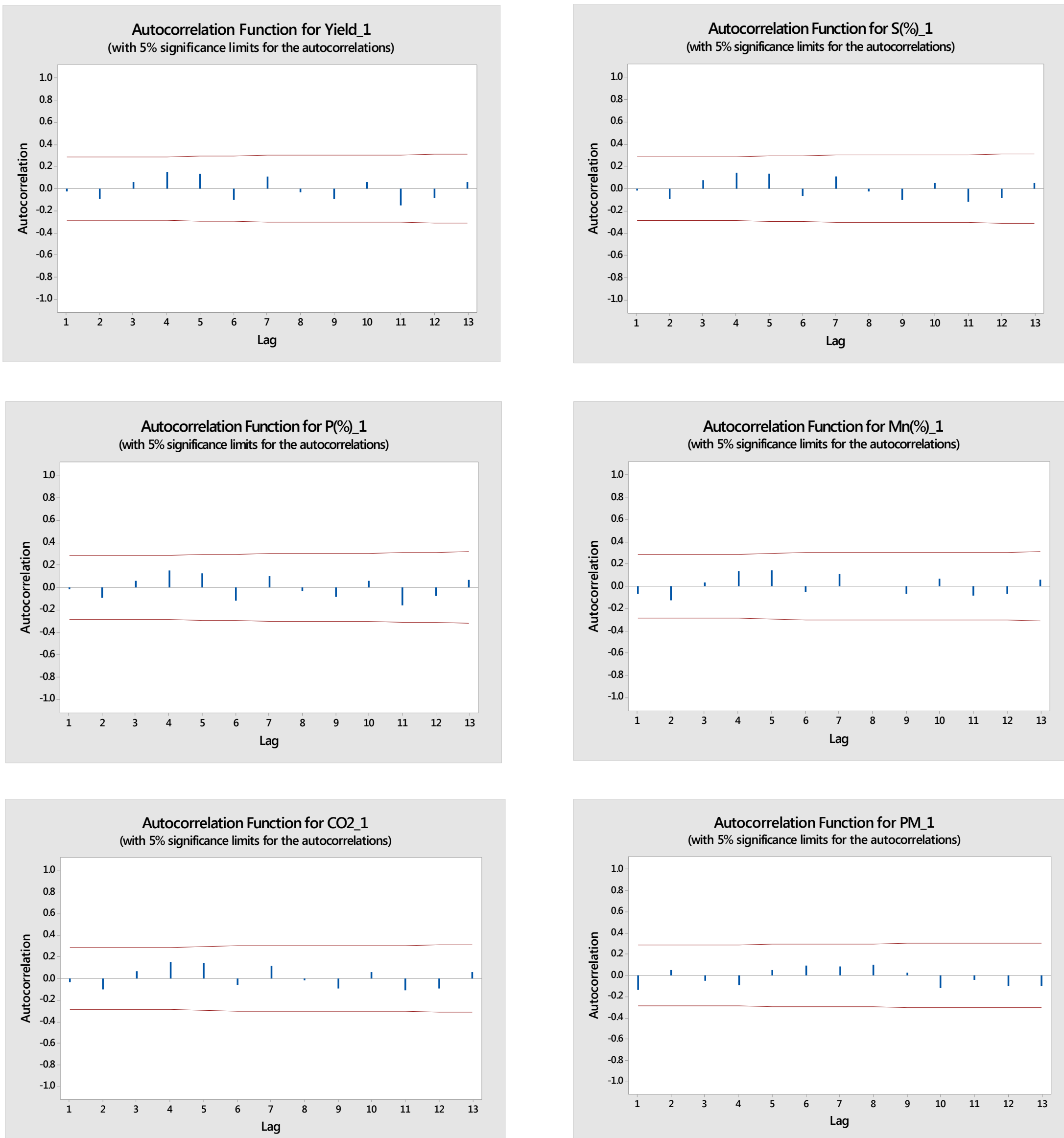

Figure-2: Auto correlation function

From the graphs it is observed that the spikes at each lag are not significant since each spike is between the significance limits, which indicates that the correlation for that lag is not present

4.1.4 Univariate charts

Minitab is employed for drawing the control charts for each quality characteristic. The control charts are shown Figure-3.

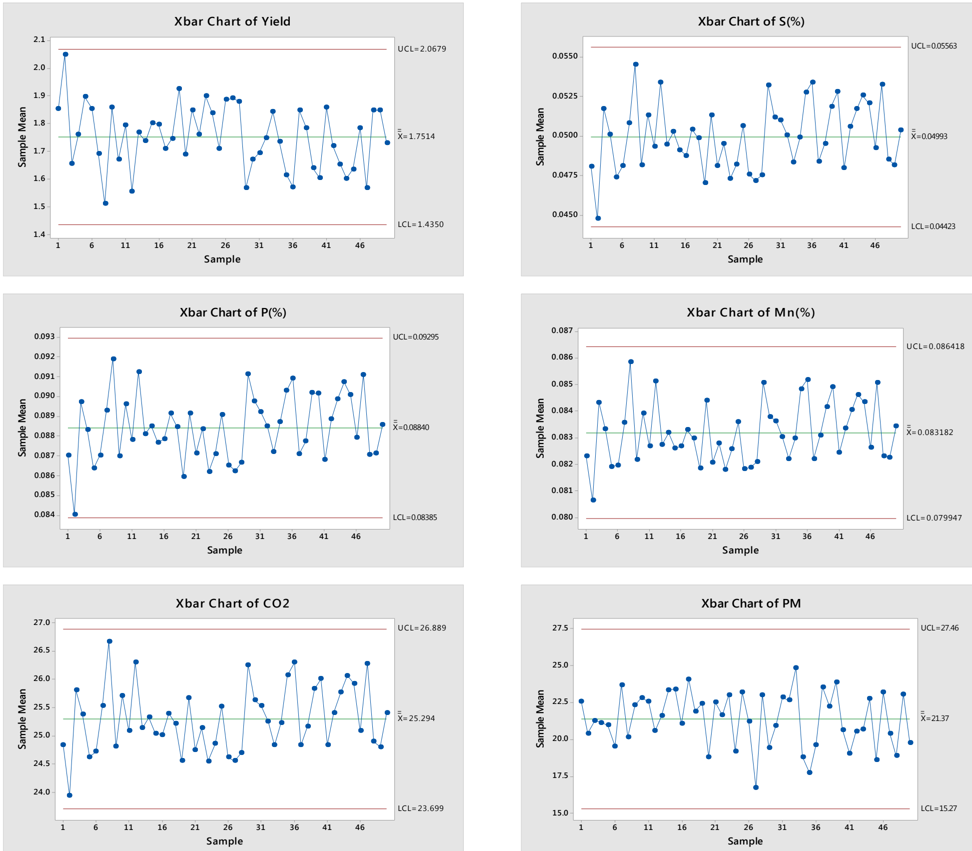

Figure-3: Control charts

From the control charts, it is observed that the process is in control since, all the points are within control limits and hence these limits are standardized for the future production and subsequent on line quality control.

4.1.5 T2 control chart for phase I

The T2 control chart was also constructed to see whether any observation containing a problematic relationship exists between parameters. The T2 control chart is plotted using Minitab 19 and is shown in Figure-4.

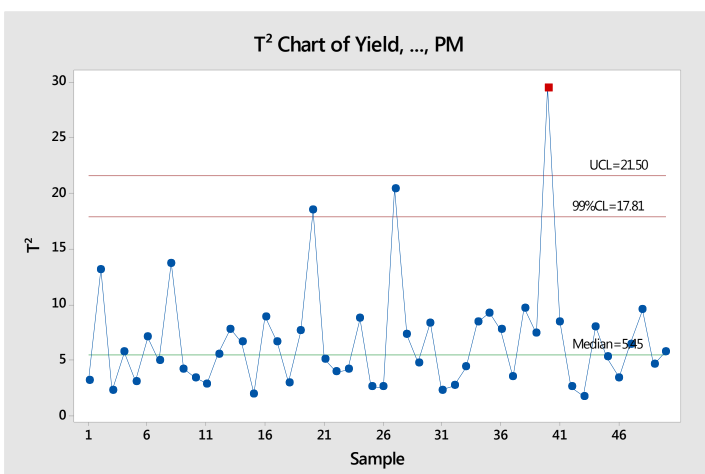

Figure-4: T2 control chart

From the Figure-4, it is observed that there is an indication of out-of-control of one subgroup (40) falls outside the control limits. T2 values of subgroup 20 and subgroup 27 below the upper control limit and above 99% confidence level. Test results for T2 chart is shown in Table-4.

Table-4: Test results for T² chart of Yield, ..., PM

	Point	Variable	P-Value
Greater Than UCL	40	Yield	0.0056
		P(%)	0.0005

From the results it is observed that Yield and %P are problematic characteristics for out of control.
The T2 control chart was constructed by deleting the problematic subgroup to obtain reference data set. The T2 control chart thus obtained is shown in Figure-5.

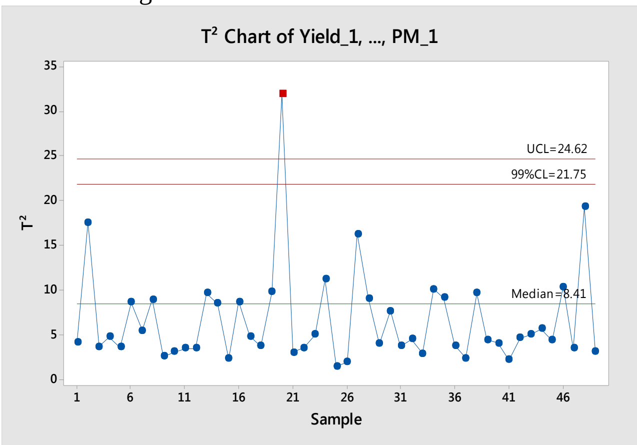

Figure-5: T2 chart of yield-1, …, PM-1

From the Figure-5, it is observed that there is an indication of out-of-control of one subgroup (20) falls outside the control limits. T2 values of all other subgroups 99% confidence level. Test results for T2 chart is shown in Table-5.

Table-5: Test results for T² chart of Yield, ..., PM

	Point	Variable	P-Value
Greater Than UCL	20	Yield	0.0263
		S(%)	0.0188
		P(%)	0.0273
		Mn(%)	0.000
		CO2	0.000

From the results it is observed that Yield, %S, %P, %Mn and CO2 are problematic quality characteristics for out of control. Again the T2 control chart was constructed by deleting the problematic subgroup to obtain reference data set. The T2 control chart thus obtained is shown in Figure-6.

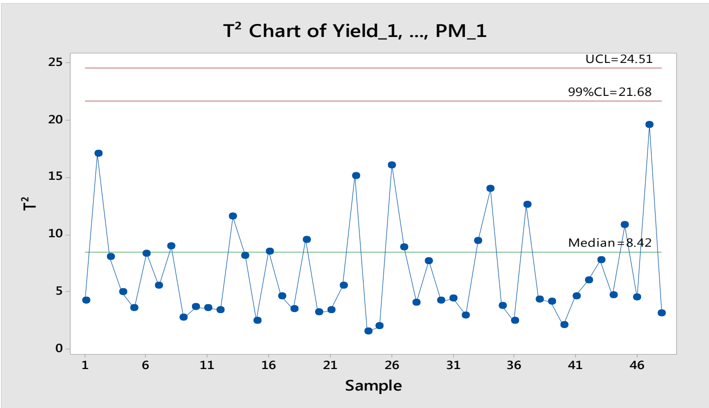

Figure-6: T2 chart of yield-1, …, PM-1

From the Figure-6, it is observed that there is no indication of out-of-control of one subgroup. T2 values of all other subgroups are also below 99% confidence level.

4.1.6 T2 control chart for phase II

In this phase T2 Control Chart limits are determined based on the mean and variance of reference data set using Minitab 18. When T2 values of new examined observation vectors exceed UCL, one can infer that observations are not in conformity with the main data set.

Data on 20 subgroups is collected as future observations as shown in Table-6.

Table-6: Subgroups data

Sub group No.	Yield	S(%)	P(%)	Mn(%)	CO2	PM
49	1.705	0.045	0.085	0.084	24.174	12.094
50	1.778	0.053	0.086	0.083	25.206	19.827
51	1.895	0.050	0.086	0.085	25.571	25.802
52	1.816	0.053	0.087	0.082	24.796	22.882
53	1.831	0.052	0.087	0.084	25.765	15.741
54	1.855	0.050	0.085	0.084	24.521	21.324
55	1.886	0.054	0.085	0.084	24.797	20.171
56	1.581	0.054	0.084	0.086	25.396	14.507
57	1.829	0.049	0.087	0.084	24.753	17.822
58	1.957	0.046	0.089	0.083	25.447	23.947
59	1.929	0.047	0.086	0.081	24.387	22.983
60	1.804	0.049	0.087	0.082	24.800	21.131
61	1.420	0.056	0.093	0.087	27.165	24.381
62	1.535	0.054	0.092	0.085	26.480	22.945
63	1.763	0.049	0.088	0.083	25.076	22.325
64	1.877	0.048	0.087	0.082	24.553	24.456
65	2.036	0.045	0.084	0.081	24.049	23.823
66	1.732	0.050	0.089	0.083	25.251	15.348
67	2.133	0.043	0.083	0.080	23.528	20.973
68	1.674	0.051	0.090	0.084	25.544	26.112

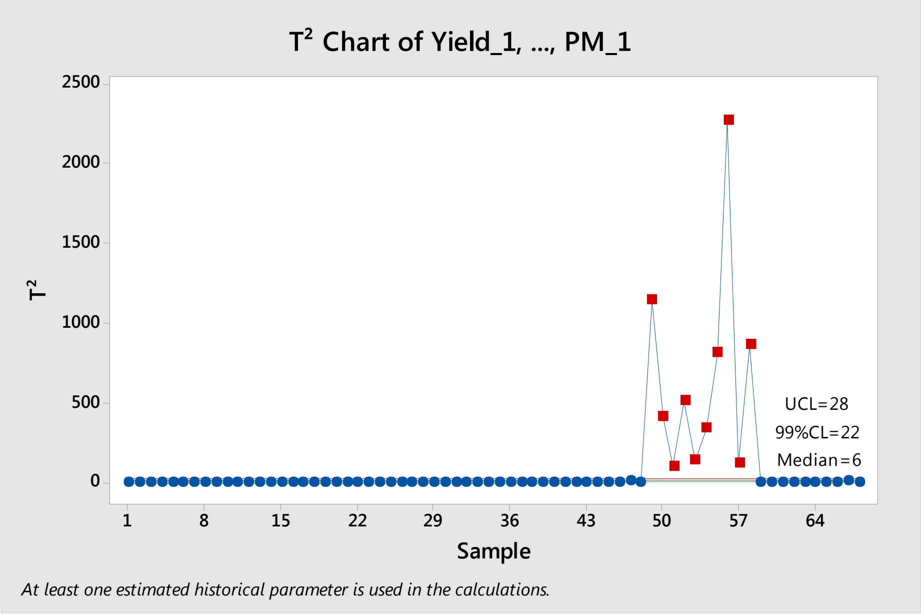

Figure-7: T2 chart of yield-1, …, PM-1

From the Figure-7, it is observed that there is an indication of out-of-control of sub groups: 49, 50, 51, 52, 53, 54, 55, 56, 57, 58 and 59 fall outside the control limits. But it is not known which variable or set of variables is responsible for it. MSPC diagnosis is useful to identify those variables.

4.1.7 Diagnosis of critical variables

When an out-of-control situation occurs by using USPC control charts, then the responsible variable(s) will reveal easily. While using T2 control chart, the diagnosis of responsible variable(s) of an out-of-control situation will require more analysis.

Diagnosis of the out-of-control observations for potential process variables are shown in Table-7.

Table-7: Diagnosis of critical process variables

S.No.	Sub Group Number	Signalled by MSPC	Potential problematic variable(s)	Variables Signalled by USPC
1	49	Out of control	Yield, S(%), P(%), and PM	PM
2	50	Out of control	Yield, S(%), P(%), and Mn	In control
3	51	Out of control	Yield, S(%), P(%), Mn, CO2	In control
4	52	Out of control	Yield, S(%), P(%), Mn, CO2	In control
5	53	Out of control	Yield, S(%), P(%), and CO2	In control
6	54	Out of control	S(%), P(%), Mn and CO2	In control
7	55	Out of control	Yield, S(%), Mn and CO2	In control
8	56	Out of control	Yield, P(%), and Mn	In control
9	57	Out of control	S(%), Mn and CO2	In control
10	58	Out of control	Yield, P(%), and Mn	In control

From the Table-7 it is noticed that for the sub groups 49, 50, 51, 52, 53, 54, 55, 56, 57 and 58 are showing out of control whereas univariate control chart showed in control except sub group 49. This out of control is due to correlation between process variables; it is to be studied further to find out root cause which process variable could be controlled to make the process stable.

4.1.8 Principal component analysis

Principal component analysis was conducted for the 10 sub-groups. In the principal component analysis, eigen values, principal components, component scores and contribution of each observation to the principal component is determined to find the contribution of the variables. The data for principal component analysis is presented in Table-8.

Table-8: Data for principal component analysis

S.No.	Sub group No.	Yield	S(%)	P(%)	Mn(%)	CO2	PM
1	49	1.705	0.045	0.085	0.084	24.174	12.094
2	50	1.778	0.053	0.086	0.083	25.206	19.827
3	51	1.895	0.050	0.086	0.085	25.571	25.802
4	52	1.816	0.053	0.087	0.082	24.796	22.882
5	53	1.831	0.052	0.087	0.084	25.765	15.741
6	54	1.855	0.050	0.085	0.084	24.521	21.324
7	55	1.886	0.054	0.085	0.084	24.797	20.171
8	56	1.581	0.054	0.084	0.086	25.396	14.507
9	57	1.829	0.049	0.087	0.084	24.753	17.822
10	58	1.957	0.046	0.089	0.083	25.447	23.947

The results of principal component analysis are presented in the following sections.

Eigen Values: Eigen values of the correlation matrix are presented in Table-9.

Table-9: Eigen values of the correlation matrix

Eigenvalue	2.7028	1.4902	0.9608	0.6109	0.1778	0.0574
Proportion	0.45	0.248	0.16	0.102	0.03	0.01
Cumulative	0.45	0.699	0.859	0.961	0.99	1

From the Table-9, it is observed that, the first two principal components have eigenvalues greater than 1. These two components explain only 69.9% of the variation in the data. Hence third principal component is also considered since the eigen value of the the principal component is very near to one (0.9608). Now these three principal components are able to explain 85.9% of variation in the data set.

Principal components: The principal components are presented in Table-10. The coefficients of the components indicate the relative weight of each variable in the component.

Table-10: Principal components

Variable	PC1	PC2	PC3	PC4	PC5	PC6
Yield	0.549	0.047	-0.078	0.362	-0.726	0.177
S(%)	-0.189	0.56	-0.618	-0.286	-0.266	-0.341
P(%)	0.528	-0.042	0.351	-0.403	-0.002	-0.658
Mn(%)	-0.386	0.347	0.472	0.556	-0.147	-0.421
CO2	0.143	0.687	0.422	-0.304	0.073	0.482
PM	0.462	0.3	-0.297	0.473	0.612	-0.099

PCA scores: PCA scores are determined and shown in Table-11. These PCA scores are utilized to determine contribution of each observation to the principal component as discussed. The contributions of each observation are presented in table.

Table-11: Contribution of each variable

Sub Group	Yield	S(%)	P(%)	Mn(%)	CO2	PM
49	0.0889	0.5564	0.0260	0.0003	0.0044	0.0273
50	0.0004	0.0029	0.0300	0.1384	0.0647	0.4850
51	0.0333	0.1499	0.0166	0.3173	0.0637	0.0146
52	0.0374	0.0006	0.0933	0.0973	0.0978	0.2572
53	0.0007	0.0816	0.0407	0.1993	0.3027	0.0008
54	0.0003	0.0222	0.0212	0.1766	0.0037	0.0067
55	0.0035	0.0089	0.0616	0.0605	0.2916	0.0362
56	0.4566	0.1338	0.0126	0.0048	0.0976	0.0343
57	0.0001	0.0384	0.0016	0.0005	0.0459	0.1379
58	0.3788	0.0053	0.0519	0.0050	0.0280	0.0000

The contributions of plot of each observation are shown in Figure-8.

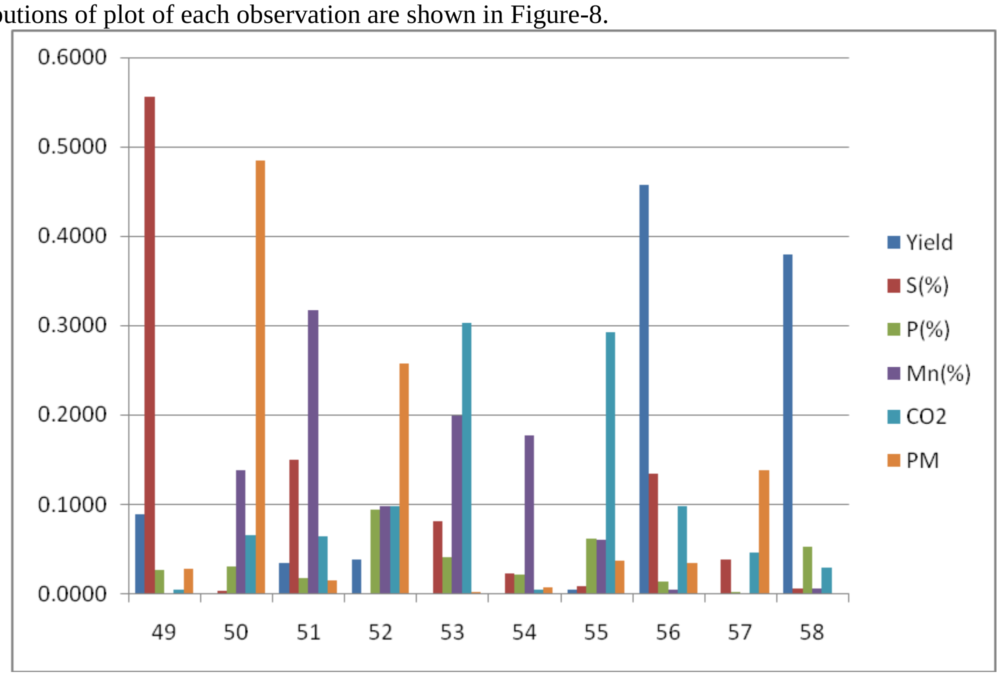

Figure-8: Overall average contribution of critical process variables

Yield:
For production of the blast furnace, decreasing the blast volume and agglomerate and increasing pulverized coal dosage can increase the hot metal yield. Increasing blast humidity can increase the hot metal yield when the blast humidity is always under a certain value. Improved hot metal yield means better production efficiency and reduced intermediate storage. If the slag is more fine-grained, it can be removed more effectively but with more iron remaining in the melt. The metal yield vary with working conditions, the use of different kinds of solid fuels, temperature and chemical heat of hot metal with higher levels of Si and Mn.
S(%):
Low sulphur in hot metal ensures lower inclusion content and enables to achieve better mechanical properties such as hot workability, impact and ductility values. Sulphur enters the furnace through coke. Though the Indian coke has less sulphur content than elsewhere, the advantage is lost due to the higher coke rate and lower slag basicity. Variation in sulphur is related to variation in slag composition in time, and during a cast in particular. The most effective method of restricting sulphur in iron is by controlling the slag basicity. In case of fluxed sinter, incorporation of dolomite in the sinter will be associated with an increased coke rate.
P(%):
Almost two-thirds of the total phosphorus input into blast furnaces comes through the iron bearing materials, while the rest comes primarily from coke. There are various ways of controlling the final phosphorus content, but the variation purely depends on raw material selection.
Mn(%):
Steel production is affected by non-availability of good quality iron ores. This increases the thrust on developing technologies and processes to utilize low grade ores. Hot metal produced using these ores results in higher manganese and lead to process abnormalities and high refractory wear in converters.
CO2:
The iron and steel industry is the largest industrial source of CO2 emissions due to the energy intensity of steel production, its reliance on carbon-based fuels and reductants, and the large volume of steel produced. Each ton of hot metal produced generates 1 ½ times of CO2. 50% of the CO2 is produced directly by the Blast furnace and balance 5% is produced by combustion of the CO in the Furnace gas. In iron ore reduction processes, a reducing agent, based on carbon and/or hydrogen, removes the oxygen from the iron oxides. CO2 is inevitably produced during reduction, and is emitted with the hot gas which exits at the top of the Blast Furnace.
PM:
Particulate matter generated in blast furnace operation is fine and coarse fractions. Coking is the major source of fine particles while materials input handling produces the majority of the coarse particles. The primary source of blast furnace emissions is the casting operation. Particulate emissions are generated when the molten iron and slag contact air above their surface. Casting emissions also are generated by drilling and plugging the tap hole. The occasional use of an oxygen lance to open a clogged tap hole can cause heavy emissions. During the casting operation, iron oxides, magnesium oxide and carbonaceous compounds are generated as particles.

V. CONCLUSION

The statistical framework proposed in the study uses multivariate statistical process control techniques to monitor multiple quality characteristics of hot metal quality simultaneously. Specifically, it employs Hotelling’s control chart to synthesize multivariate measurement series to a scalar series that is convenient to compute, compare, visualize and manage. In addition, principal component analysis technique is adopted to find plausible causes for the out-of-control signals in the control chart. The study is implemented with a case study of smelting operation of blast furnace of an integrated steel plant to monitor the complex process effectively.

When there is more than one quality characteristic is to be monitored, it is advisable to use MSPC charts to avoid false signals associated with using separate USPC charts. This study explores problems in process monitoring of variables with USPC charts. The production of hot metal is a very complex process, where more number of variables are correlated with each other, monitoring simultaneously with USPC charts having the problem of interpreting an out-of-control signal. Hence it was further studied with the application MSPC charts. Further detecting contribution of critical process variables is difficult with MSPC charts and needs further investigation. For that we recommend to apply principal components analysis for further analysis. The same technique is applied in this study and reduced the number of critical process variable to potential responsible variables to reduce the redundancy in measuring. The findings indicate a clear distinction between USPC and MSPC.

The sample is very small proportion and research studies with much larger sample size would be required to ensure appropriate generalization of the findings of the study. This case study is focused only on quality characteristics of hot metal production process. The future research aimed to apply the Six Sigma methodology in these areas to obtain continuous quality improvement.

VI. REFERENCES

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