Application of Univariate Statistical Process Control Charts for Improvement of Hot Metal Quality- A Case Study

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Abstract

Statistical Process Control (SPC) techniques are employed to monitor production processes over time to detect changes. The basic fundamentals of statistical process control and control charting were proposed by Walter Shewhart. Shewhart $\bar{X}$ chart can be used for monitoring both the mean and the variance of a process, however sensitivity of $\bar{X}$chart to shifts in the variance is often considered inadequate. So, it is common to use the $\bar{X}$chart coupled with either R chart or S chart, to monitor changes in mean and variance of process. This paper presents the application of univariate control chart for monitoring hot metal making process in a blast furnace of a steel industry for continuous quality improvement.

Key Words - *Control Chart, Regression Analysis, Statistical Process Control, Univariate, $\bar{X}$ chart*

Introduction

Statistical process control is defined as the application of statistical techniques to control a process. SPC is concerned with quality of conformance. There are a number of tools available to the quality engineer that is effective for problem solving process. The seven quality tools are relatively simple but very powerful tools which every quality engineer should aware. The tools are: flow chart, run chart, process control chart, check sheet, pareto diagram, cause and effect diagram, and scatter diagram (Juran&Gryna, 1998) [1].

The primary function of a control chart is to determine which type of variation is present and whether adjustments need to be made to the process. Variables data are those data which can be measured on a continuous scale. Variable data are plotted on a combination of two charts- usually a $\bar{X}$ chart and a range (R) chart. The $\bar{X}$ chart plots sample means. It is a measure of between-sample variation and is used to assess the centering and long term variation of the process. The range chart measure the within sample variation and asses the short term variation of the process.

A control chart is a statistical tool used to distinguish between variation in a process resulting from common causes and variation resulting from special causes. It presents a graphic display of process stability or instability over time. Every process has variation. Some variation may be the result of causes which are not normally present in the process. This could be special cause variation. Some variation is simply the result of numerous, ever-present differences in the process. This is common cause variation. Control Charts differentiate between these two types of variation. One goal of using a Control Chart is to achieve and maintain process stability. Process stability is defined as a state in which a process has displayed a certain degree of consistency in the past and is expected to continue to do so in the future. This consistency is characterized by a stream of data falling within control limits based on plus or minus 3 Sigma (standard deviation) of the centerline. Control charts are useful, i) To monitor process variation over time ii) To differentiate between special cause and common cause variation iii) To assess the effectiveness of changes to improve a process iv) To communicate how a process performed during a specific period. There are different types of control charts, and the chart to be used is determined largely by the type of data to be plotted. Two important types of data are: Continuous (measurement) data and discrete (or count or attribute) data. Continuous data involve measurement. Discrete data involve counts (integers). For continuous data that are $\bar{X}$ chart, R chart are often appropriate.

SPC is founded on the principle that a process will demonstrate consistent results unless it is performed inconsistently. Thus, we can define control limits for a consistent process and check new process outputs in order to determine whether there is a discrepancy or not. In the manufacturing arena, it is not difficult to figure out the relationship between product quality and the corresponding production process. Therefore we can measure process attributes, work on them, improve according to the results and produce high quality products. There is a repetitive production of the same products in high numbers and this brings an opportunity to obtain large sample size for the measured attributes. Moreover, the product is concrete, and the attributes and variables to be measured are easily defined. Consequently, the only difficulty left is to define correct attributes and collect data for utilizing the tools of Statistical Process Control.

Literature review

Many businesses use Univariate Statistical Process Control (USPC) in both their manufacturing and service operations. Automated data collection, low-cost computation, products and processes designed to facilitate measurement, demands for higher quality, lower cost, and increased reliability have accelerated the use of USPC.

A more modern approach for monitoring process variability is to calculate the standard deviation of each subgroup and use these values to monitor the process standard deviation (Montgomery & Runger, 2003)[2]. Samanta and Bhattacherjee (2004)[3] analyzed quality characteristic through construction of the Shewart control chart for mining applications. Woodall and Faltin, F. W. (1993) [4] presented an overview and perspective on control charting. The role of SPC in understanding, modeling, and reducing variability over time remains very important. Weller (2000) [5] discussed some practical applications of Statistical Process Control. Mohammed (2004) [6] adopted Statistical Process Control to improve the quality of health care. Mohammed et al.,(2008) [7] illustrated the selection and construction of four commonly used control charts(xmr-chart, p-chart, u-chart, c-chart) using examples from healthcare. Grigg et al., (1998)[8] presented a case study Statistical Process Control in fish product packaging. Srikaeo, K., & Hourigan, J.A. (2002) [9] discussed the use Statistical Process Control to enhance the validation of critical control points (CCPs) in shell egg washing. Rashed (2005) [10] made a performance Analysis of Univariate and Multivariate Quality Control Charts for Optimal Process Control. Statistical Process Control involves measurements of process performance that aim to identify common and assignable causes of quality variation and maintain process performance within specified limits. (Mukbelbaarz, 2012)[11]. Sharaf El-Din et al (2006) [12], made a comparison of the univariate out-of-control signals with the multivariate out-of-control signals using a case study of Steel making.

Methodology

3.1 Identification of critical process variables

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 appropriately to be monitored. The critical process variable of the process may be identified by Regression Analysis. Regression analysis is a statistical technique for estimating the relationships among variables in process and to predict a dependent variable(s) from a number of input variables.

T-Statistics is an aid in determining whether an independent variable should be included in a model or not. A variable is typically included in a model if it exceeds a pre-determined threshold level or ‘critical value’. Thresholds are determined for different levels of confidence. For e.g. to be 95% confident that a variable should be included in a model, or in other words to tolerate only a 5% chance that a variable doesn’t belong in a model, a T-statistic of greater than 1.98 (if the coefficient is positive) or less than -1.98 (if the coefficient is negative) is considered statistically significant.

3.2 Construction of Control Charts

To produce with consistent quality, manufacturing processes need to be closely monitored for any deviations in the process. Proper analysis of control charts that are used to determine the state of the process not only requires a thorough knowledge and understanding of the underlying distribution theories associated with control charts, but also the experience of an expert in decision making. There are many different types of control chart and the chart to be used is determined largely by the type of data to be plotted. This paper formulates Shewhart mean ($\bar{X}$) and R- Chart for diagnosis and interpretation.

Case study

The hot metal production process in Blast Furnace of an integrated Steel Plant is shown in Fig. 1. The purpose of a blast furnace is to chemically reduce and physically convert iron oxides into liquid iron called "hot metal". The blast furnace is a huge, steel stack lined with refractory brick, where the inputs are iron ore, sinter, coke and limestone are dumped into the top, and preheated air (sometimes with Oxygen Enrichment) is blown into the bottom.

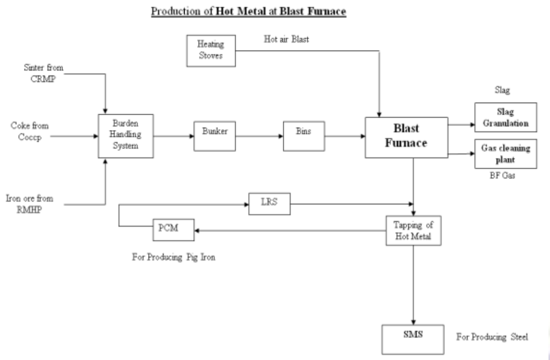

Fig.1: Process flow diagram of Hot Metal process in Blast Furnace

In which, inputs like sinter, coke are pre-processed before using in Blast Furnace. The hot air that was blown into the bottom of the furnace ascends to the top after going through numerous chemical reactions. These raw materials require 6 to 8 hours to descend to the bottom of the furnace where they become the final product of liquid iron and slag. The output liquid iron known as hot metal drained from the furnace at regular intervals from the bottom through tap hole.

The hot metal with lower silicon and Sulphur contents is required for the production of Steel at Steel Melt Shop. Blast Furnace is supposed to supply the hot metal with the following composition to reduce defectives in Steel making at Steel Melt Shop (SMS).

Silicon (Si) = 0.3 - 0.60%
Manganese (Mn) = 0.0 - 0.25%
Phosphorous (P) = 0.0 - 0.15%
Sulphur (S) = 0.0 - 0.04%

To produce desired quality hot metal, it is essential to identify the critical process variable from the given inputs and optimize them.

The various inputs for this process are Blast Volume (M^3/Min), Blast Pressure (Kg/cm^2), Blast Temperature (^{0}C), Steam (t/hr.), Oxygen Enrichment(%), Oxygen (M^3/hr.), Ash, Moisture, Volatile material, Fe(%),FeO (%), SiO_2(%), Al_2O_3(%), CaO (%), MgO (%), Mn (%), SiO, Sulpher (S), Phosphorus(P), Manganese (Mn), Silica(Si), MnO (%) etc. The production data with 370 observations grouped by 46 days was collected for the study.

Results & Discussion

5.1 Identification of critical process variables

In order to understand the relationship between the input and output variables of the hot metal, the data is analyzed and Regression analysis has been carried out with the help of MINITAB software. In the analysis, each output variable is tested individually to find out relationship between input process variables. A set of data containing observations on 370 samples were analyzed. The regression equation for each output variable is as follows:

(1) The regression equation for Silicon to input variables is

Si = - 36.8 - 0.000016 Blast Volume (M^3/Min) + 0.864 Blast Pressure (Kg/cm^2)- 0.830 Top Pressure (Kg/cm^2) - 0.00130 Blast Temp (^{o}C) + 0.00413 Steam (t/hr) + 0.0402 % Oxygen Enrichment - 0.000014 Oxygen (M^3/hr.) + 0.420 Ash - 0.154 Moist + 0.524 VM + 0.389 FC - 0.0165 %Fe + 0.0397 %FeO- 0.372 %SiO_2 + 0.793 %Al_2O_3 + 0.0609 %CaO - 0.0220 %MgO + 0.973 %Mn- 4.16 SiO_2

Table 1. T & P values for Silicon.

Predictor	T	p
Constant	-0.47	0.636
Blast Volume	-0.24	0.811
Blast Pressure	1.89	0.06
Top Pressure	-1.75	0.08
Blast Temp	-3.34	0.001
Steam (t/hr)	1.18	0.239
Oxygen Enrichment	0.69	0.493
Oxygen	-0.85	0.397
Ash	0.55	0.586
Moist	-1.06	0.291
VM	0.67	0.501
FC	0.5	0.616
%Fe	-0.24	0.814
%FeO	2.55	0.011
%SiO_2	-3.66	0.000
%Al_2O_3	3.36	0.001
%CaO	1.1	0.271
%MgO	-0.33	0.739
%Mn	3.19	0.002
SiO_2	-3.09	0.002

(2) The regression equation for Manganese to input variables is

Mn = - 7.00 + 0.000012 Blast Volume (M^3/Min) - 0.0169 Blast Pressure (Kg/cm^2) - 0.0141 Top Pressure (Kg/cm^2) + 0.000314 Blast Temp (^{o}C) + 0.000390 Steam (t/hr) - 0.0115 % Oxygen Enrichment + 0.000003 Oxygen (M^3/hr.) + 0.0622 Ash - 0.0049 Moist + 0.106 VM + 0.0746 FC - 0.00946 %Fe + 0.00173 %FeO - 0.0406 %SiO_2 + 0.0784 %Al_2O_3 + 0.0166 %CaO - 0.0233 %MgO + 0.141 %Mn - 0.187 SiO_2

Table 2. T & P values for Manganese.

Predictor	**T**	**p**
Constant	-0.73	0.465
Blast volume	1.43	0.154
Blast Pressure	-0.3	0.765
Top Pressure	-0.24	0.81
Blast Temp	6.55	0.000
Steam (t/hr)	0.9	0.367
Oxygen Enrichment	-1.59	0.113
Oxygen	1.54	0.125
Ash	0.65	0.513
Moist	-0.27	0.787
VM	1.11	0.269
FC	0.78	0.435
%Fe	-1.1	0.274
%FeO	0.9	0.369
$\%SiO_2$	-3.23	0.001
$\%Al_2O_3$	2.69	0.007
%CaO	2.44	0.015
%MgO	-2.87	0.004
%Mn	3.74	0.000
SiO_2	-1.13	0.261

(3) The regression equation for Sulpher to input variables is
S = - 0.88 + 0.000009 Blast Volume (M^3/Min) - 0.0490 Blast Pressure (Kg/cm^2) + 0.0459 Top Pressure (Kg/cm^2) + 0.000013 Blast Temp (^oC) - 0.00116 Steam (t/hr) - 0.00924 % Oxygen Enrichment + 0.000002 Oxygen (M^3/hr.) + 0.0088 Ash + 0.0102 Moist - 0.0075 VM + 0.0076 FC + 0.00305 %Fe - 0.00090 %FeO + 0.00167 $\%SiO_2$ + 0.0120 $\%Al_2O_3$ - 0.00326 %CaO + 0.00840 %MgO + 0.0575 %Mn - 0.0846 SiO_2

Table 3. T & P values for Sulpher.

Predictor	**T**	**p**
Constant	-0.16	0.874
Blast Volume	1.86	0.064
Blast Pressure	-1.51	0.132
Top Pressure	1.37	0.173
Blast Temp	0.49	0.626
Steam	-4.66	0.000
Oxygen Enrichment	-2.22	0.027
Oxygen	2.15	0.032
Ash	0.16	0.872
Moist	0.98	0.328
VM	-0.14	0.892
FC	0.14	0.89
%Fe	0.61	0.539
%FeO	-0.81	0.418
$\%SiO_2$	0.23	0.818
$\%Al_2O_3$	0.72	0.474
%CaO	-0.83	0.406
%MgO	1.8	0.073
%Mn	2.66	0.008
SiO_2	-0.89	0.377

(4) The regression equation for Phosphorous to input variables is
P = - 3.16 + 0.000023 Blast Volume (M^3/Min) - 0.0421 Blast Pressure (Kg/cm^2) + 0.0115 Top Pressure (Kg/cm^2) - 0.000071 Blast Temp (^oC) + 0.000868 Steam (t/hr) - 0.00572 % Oxygen Enrichment + 0.000000 Oxygen (M^3/hr.) + 0.0323 Ash - 0.0026 Moist + 0.0276 VM + 0.0358 FC - 0.00458 %Fe - 0.00238 %FeO + 0.00923 $\%SiO_2$ - 0.0139 $\%Al_2O_3$ + 0.00114 %CaO - 0.0114 %MgO - 0.0404 %Mn + 0.182 SiO_2

Table 4. T & P values for Phosphorus.

Predictor	**T**	**p**
Constant	-0.43	0.668
Blast Volume	3.62	0.000
Blast Pressure	-0.97	0.332
Top Pressure	0.26	0.798
Blast Temp	-1.93	0.055
Steam	2.61	0.009
Oxygen Enrichment	-1.03	0.304
Oxygen	0.14	0.887
Ash	0.44	0.659
Moist	-0.19	0.853
VM	0.37	0.708
FC	0.49	0.626
%Fe	-0.69	0.491
%FeO	-1.61	0.109
%SiO2	0.95	0.341
$\%Al_2O_3$	-0.62	0.536
%CaO	0.22	0.828
%MgO	-1.83	0.067
%Mn	-1.4	0.163
SiO_2	1.42	0.155

It is also necessary to examine the dependency between these variables and also find the critical process variables (p value < 0.05) which may influence the quality of hot metal. The 'p' and 'T' values from the Table 1 to Table 4 of the regression analysis are tabulated in Table 5 for which 'p' value is less than 0.05. It is predicted from the above, the critical process variables which may influence the quality of Hot metal in this process are Blast Volume, Blast Pressure, Steam, Oxygen Enrichment, Oxygen, %FeO, %MgO, %Mn, SiO_2 and $\%Al_2O_3$.

The T-statistic values for the above critical process variables are also higher than the threshold values (i.e. plus or minus 1.98 for 95 % confidence level) indicating their significance presence of dependence which may influence the quality of Hot metal.

Table 5. Diagnosis of critical process variables

Predictor Variable	T	p
Blast Volume	3.62	0.000
Blast Pressure	-3.34	0.001
Steam (t/hr)	2.61	0.009
Oxygen Enrichment	-2.22	0.027
Oxygen	2.15	0.032
%FeO	2.55	0.011
%MgO	2.44	0.015
%Mn	2.66	0.008
SiO_2	-3.09	0.002
$\%Al_2O_3$	3.36	0.001

5.2 Control limits and construction of Control charts

The data has been analyzed using $\bar{X}$ chart with customary plus/minus three sigma control limits to identify the problematic observations. The individual Control charts for the critical process variables are drawn and shown (Fig.2 to Fig. 11).

$\bar{X}$ Chart of Blast Volume is shown in Fig.2 and the observations on the days of 9, 25 and 45falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of Blast Pressure is shown in Fig.3 and the observations on the days of 9, 25, 45 and 46 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of Steam is shown in Fig.4 and the observations on the days of 6, 15, 25, 32, 35and 45 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of % Oxygen Enrichment is shown in Fig. 5 and the observations on the days of 7, 35, 36, 37, 38, and 45 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of Oxygen is shown in Fig. 6 and the observations on the days of 7, 35, 36, 37, 38, and 45 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of % FeO is shown in Fig. 7 and the observations on the days of 5, 13, 14, 17, 18, and 22 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of %MgO is shown in Fig. and the observations on the days of 10, 20, 21, 22, 29, 30, 34, 35, 40, 42, and 45 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of %Mn is shown in Fig. 9 and the observations on the days of 31, 32, 33, 34, 35, 40, 45 and 46 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of $SiO_2$is shown in Fig. 10 and the observations on the days of 1, 12, 13, 14, 30, 33 and 46 falls outside the control limits, indicating an unstable process. Test Results for $\bar{X}$ Chart of $\%Al_2O_3$is shown in Fig. 11 and the observations on the days of 15, 19, 20, 40, 42, 45 and 46 falls outside the control limits, indicating an unstable process.

The input values for Blast Volume, Blast Pressure, Steam, Oxygen Enrichment and Oxygen remain unchanged for the entire day and there is no difference in sample range with in a day. Hence the significance of R- Chart does not exist for these variables. It is evident from the R-Chart drawn for the above variables in the Fig. 2 to Fig. 6 that many of the observations fall outside control limits, hence ignored.

Whereas the input values of other variables like %FeO, %MgO, %Mn, SiO_2, and $\%Al_2O_3$ may vary for each observation and corresponding R- Charts were drawn and shown in the Fig.7 to Fig.11 respectively. The out of control limit points for MgO is on 46th day, for Mn is on 10th day, for SiO_2 is on 3rd and 30th day and for $\%Al_2O_3$ is on 4th , 8th , 10th , 37th and 46th days.

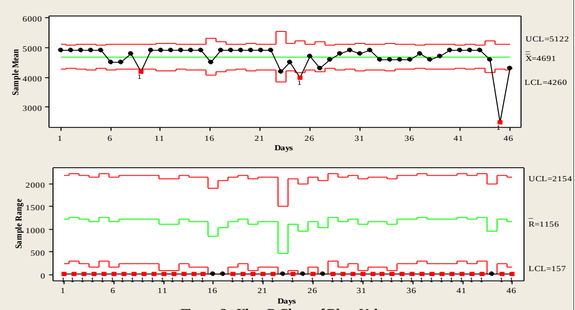

Figure 2. Xbar-R Chart of Blast Volume

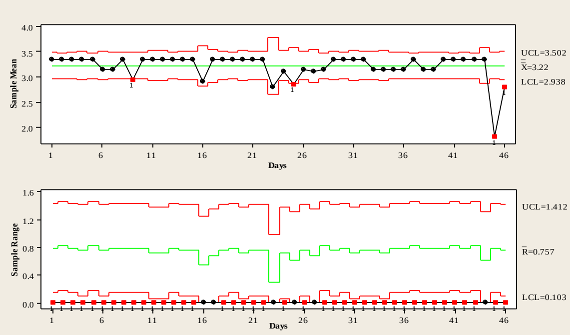

Figure 3. Xbar-R Chart of Blast Pressure

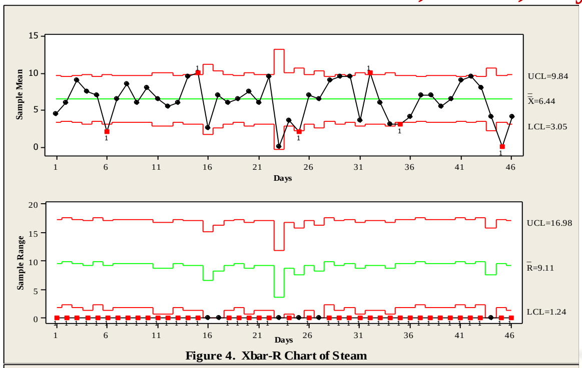

Figure 4. Xbar-R Chart of Steam

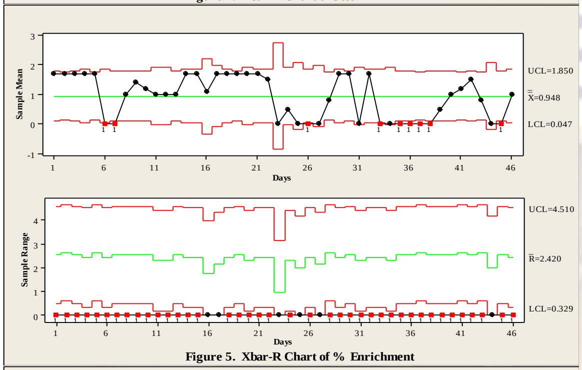

Figure 5. Xbar-R Chart of % Enrichment

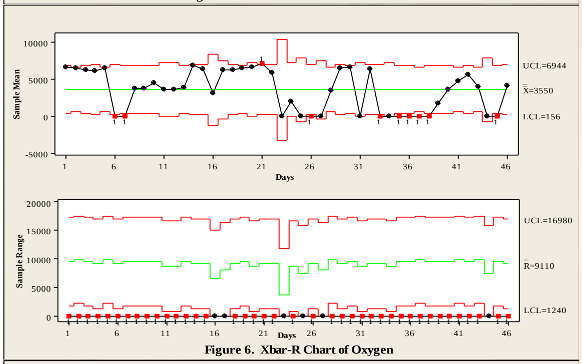

Figure 6. Xbar-R Chart of Oxygen

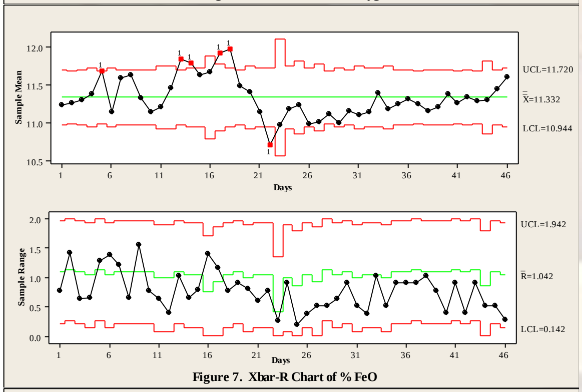

Figure 7. Xbar-R Chart of % FeO

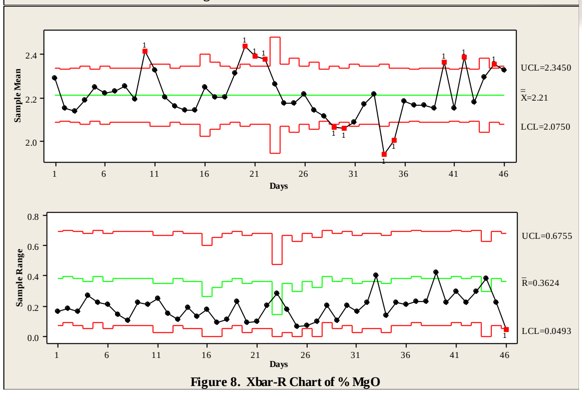

Figure 8. Xbar-R Chart of % MgO

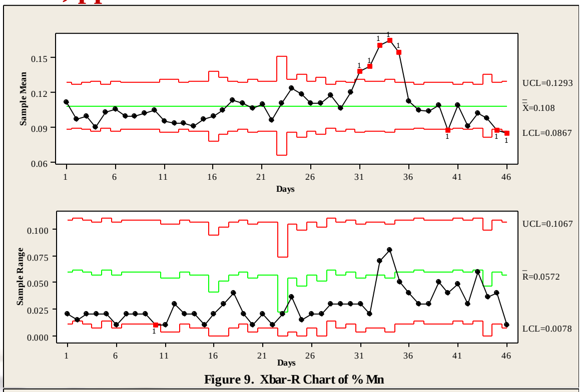

Figure 9. Xbar-R Chart of % Mn

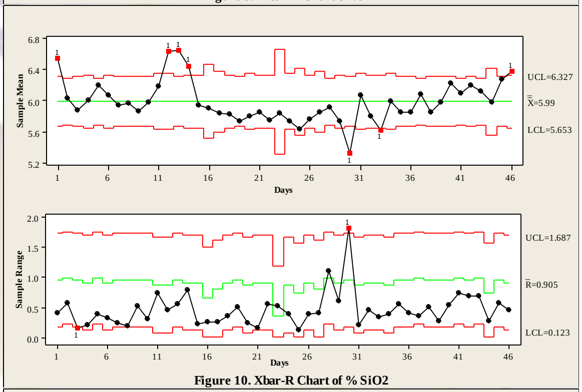

Figure 10. Xbar-R Chart of % SiO2

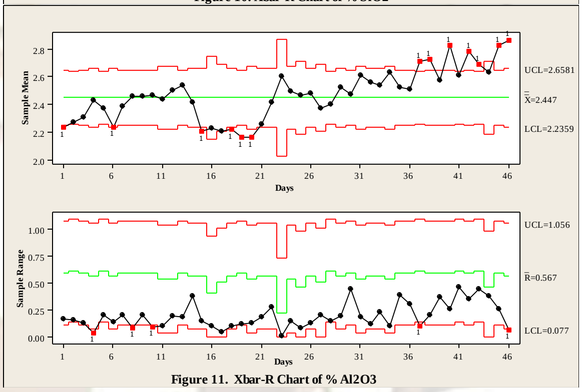

Figure 11. Xbar-R Chart of % Al2O3

5.3 Results and discussion

Even if the variation in input variables were known but the exact reason was difficult to identify due to complexities in Blast Furnace Process. Blast furnace slag composition has very important behavior on its physicochemical characteristics which affects the degree of desulphurization, smoothness of operation, coke consumption, hot metal productivity and its quality.

Al_2O_3, MgO and CaO that entered with the iron ore, pellets, sinter or coke Si with the coke ash and Sulphur enters through coke. In the normal practice of blast furnace, slag is generally accounted for by adjusting the overall composition of CaO, SiO_2, Al_2O_3 and MgO components. Since the limestone (flux) is melted to become the slag which removes Sulphur and other impurities, the blast furnace operator may blend the different grades of flux to produce the desired slag chemistry and produce optimum hot metal quality. High top pressure in Blast Furnaces can decrease % of Si in hot metal. An increase in the Fe content of sinter may optimizes the Carbon/ Sulpher ratio and decrease in Al_2O_3 content in hot metal. Manganese reaction is always accompanied by silica reaction. By adding additional SiO_2 can reduce % Mn content in hot metal. By implementing these steps may lead to reduce the defectives in the output and improves the quality of hot metal

Conclusion

This paper explores monitoring of variables that effects hot metal making in an integrated steel plant. In the first phase critical process variables that affect the quality of hot metal are identified through regression analysis. From the study the variables namely, Blast Volume, Blast Pressure, Steam,% Enrichment, Oxygen, %FeO, %MgO, %Mn, SiO_2, and %Al_2O_3 are identified as critical process variables. Subsequently $\bar{X}$ and R-Charts are drawn to monitor these critical process variables.

When the more number of variables are correlated with each other, univariate control charts are difficult to manage and analyze because of the large numbers of control charts of each process variable. An alternative approach is to construct a single multivariate T^2 control chart that minimizes the occurrence of false process alarms. Hence this study may be extended to multivariate control charts that monitor the relationship between the variables and identifies real process changes which are not detectable through univariate charts.

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