International Journal for Quality Research 7(4) 623–640
ISSN 1800-6450

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Article info:
Received 23 December 2012
Accepted 4 November 2013

UDC – 65.012.7

APPLICATION OF MULTIVARIATE CONTROL CHART FOR IMPROVEMENT IN QUALITY OF HOTMETAL - A CASE STUDY

Abstract: *Quality of hot metal produced in a blast furnace is affected by multiple variables. Classical Statistical Process Control (SPC) methodologies are non-optimal to monitor and control these multiple variables as the effect of one variable can be confounded with effects of other correlated variables. Further, 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. Multivariate control charts monitor the relationship between the variables and identifies real process changes which are not detectable with Univariate charts. This paper studies the application of Multivariate Statistical Process Control (MSPC) charts to monitor hot metal production process in a steel industry.* T^2 *diagnosis with Principal component analysis (PCA) is applied to analyze the critical process variables.*

Keywords: *Control Chart, Regression Analysis, Statistical Process Control, Univariate, Multivariate, Principal Component Analysis, Correlation*

1. Introduction

Today iron and steel products are highly valued and they are vital to Nation's economy & indispensable in many product applications. The Steel along with Power form back bone of the national development. In general, steel industry is envisaged to continue to play a larger role in all spheres of development in India considering low per capita consumption of steel and in particular, in infrastructure development of the nation. In the recent times, the steel industry has seen tough competition in domestic as well as global market with reference to quality and cost. While no stone is being left unturned to achieve the highest grades of qualities in our steel production, we are looking for all avenues of quality controlling measures. Unless the plant competes in quality aspect, it will be difficult to remain in the race of domestic as well as global market. The purpose of the paper is to provide an insightful research and examination of the methodology and implementation of MSPC charts in the process of hot metal production in a Blast furnace.

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2. Literature review

2.1 Statistical process control

In large and complex manufacturing systems, statistical methods are used to monitor whether or not the processes remain in control. Control charts are widely used as process monitoring tools, primarily to detect changes in the process mean or in its standard deviation, which can indicate deterioration in quality. Statistical Process Control has become an important approach for process industries since 1920s. The aim of SPC is to achieve higher product quality and lower production cost by minimizing the defects. In general, statistical process control techniques help us to monitor the production process and to detect abnormal process behavior due to special causes. Once the special causes for abnormal process behavior is detected and further eliminated, the process can be improved, so as the quality of the product. To monitor the production process W. A. Shewhart developed the statistical process control chart (Shewhart, 1931). This is also known as Univariate Statistical Process Control (USPC) chart.

Quality is generally determined by several quality characteristics which may be correlated. Each of these quality characteristics must satisfy certain specifications. The quality of the product depends on the combined effect of many input variables rather than their individual values. However, USPC can only monitor single process variable at a time. The signal interpretation in this control chart is straightforward as it ignores the relationship to the other variables within the process. The standard assumptions in SPC are that the observed process values are normally, independently and identically distributed with fixed mean and standard deviation when the process is in control. Due to the dynamic behavior, these assumptions are not always valid.

In reality, manufacturing systems are often influenced by many known or unknown disturbances (Box and Kramer, 1992). The modern production process is integrated and has become more complex, inevitably that the number of process variables need to be monitored has increased dramatically. Monitoring the process variables individually ignores the possible correlation or interaction between them. This can lead to missed out-of-control signals. When the number of quality characteristics are more, the application of USPC may be inappropriate.

To monitor such situations Multivariate Statistical Process Control charts namely T^2 charts, T^2 Generalized Variance charts, Multivariate EWMA charts etc., are powerful tools. This method considers the correlation between variables and monitors more than one variable simultaneously. MSPC chart takes this correlation of process variables into account in monitoring by the mean vector or covariance matrix. By monitoring the relationship between variables, MSPC reflects the process situation more precisely and is able to detect the out-of-control situation. Early work on multivariate statistical control procedures was performed in the 1930's and in the 1940's (Hotelling, 1947).

2.2 Multivariate statistical process control charts

It is a fact of life that most data are naturally multivariate. Quality control problems arise when processes or products with two or more related quality variables are to be monitored or controlled. When these variables are correlated, a more appropriate approach would be required to monitor them simultaneously. It is very likely that these variables will be correlated due to the large number of variables collected at a given time. Consequently, multivariate statistical methods, which provide simultaneous scrutiny of several variables, are needed for monitoring and diagnosis purposes in modern manufacturing systems. A more appropriate method of detecting and isolating process faults is to utilize Multivariate Statistical Process Control (MSPC) approaches

Hotelling(1947) introduced a statistic which uniquely lends itself to plotting multivariate observations. This statistic, appropriately named Hotelling's T^2, is a scalar that combines information from the dispersion and mean of several variables. Due to the fact that computations are laborious and fairly complex and require some knowledge of matrix algebra, acceptance of multivariate control charts by industry was slow and hesitant.

As in the Univariate case, when data are grouped, the T^2 chart can be paired with a chart that displays a measure of variability within the subgroups for all the analyzed characteristics. The combined T^2 and dispersion charts are thus a multivariate counterpart of the Univariate and S (or and R) charts.

Kourti and MacGregor (1996) monitored both process and product through multivariate statistical process control. Woodall and Montgomery (1999) emphasized the need for much more research in this area since most of the processes involve a large number of variables that are correlated. Mason and Young (2001) implemented multivariate statistical process control using Hotelling's T^2 statistic. Mason *et al*. (2003) interpreted the patterns of process behavior occurring in Shewhart control charts as indicators of extraneous sources of process variation. The authors concluded that the process will be improved if the cause of systematic pattern in the process are diagnosed and further eliminated.

Kourti (2005) overviewed the latest developments in multivariate statistical process control (MSPC) and its application for fault detection and isolation (FDI) in industrial processes and elaborated the methodology and describes how it is transferred to the industrial environment. Kim and Reynold (2005) proposed Multivariate monitoring using an multivariate exponentially weighted moving average (MEWMA) control chart with unequal sample sizes.

Panyaping (2006) considered an application of the multivariate analysis technique as a management tool to characterize the relationships between wastewater generation and production conditions in the manufacture of textile products of Textile Industry in Samutprakarn Province. Sharaf El-Din *et al.* (2006) made a study on the application of Univariate and multivariate control charts for quality improvement in steelmaking. Huwang*et al*. (2007) considered individual observations for Monitoring Multivariate Process Variability. Changand Zhang (2007) tried a very complicated problem of monitoring variance shift in multivariate time series and proposed multivariate EWMA charts called MEWMV charts.

Li *et al*. (2008) considered Causation based T^2 decomposition for Multivariate Process Monitoring and Diagnosis. Zhang and Chang (2008) proposed a new single control chart which integrates the exponentially weighted moving average (EWMA) procedure with the generalized likelihood ratio (GLR) test for jointly monitoring both the multivariate process mean and variability. He *et al*. (2008) proposed self-starting control charts to reduce the bias of the Shewhart chart for the case with unknown process mean and variance.

Haridy and Wu (2009) discussed in their paper about the characterization of the dynamic behavior of the manufacturing process with the appropriate monitoring procedures; and the development of adaptive monitoring procedures for the processes with a comparison between Univariate and multivariate control charts. Zou and Qiu (2009) proposed a new technique LASSO-based multivariate test statistic, then integrated with multivariate EWMA charting scheme for process monitoring. This approach balances protection against various shift levels and shift directions, and hence provides an effective tool for multivariate SPC applications.

Zhang *et al*. (2010) proposed a new multivariate charting scheme for simultaneously monitoring the process mean vector and covariance matrix of a multivariate normal process by using a single chart. Waterhouse *et al*. (2010) considers the implementation and performance of the T^2, multivariate exponentially weighted moving average (MEWMA) and multivariate cumulative sum (MCUSUM) charts in light of the challenges faced in clinical settings. Sinha *et al*. (2010) proposed and explored a multivariate logistic regression model for analyzing multiple binary outcomes with incomplete covariate data where auxiliary information is available. Shao *et al*. (2011) proposed the combination of statistical process control with engineering process control with binomial distribution concept to effectively determine the starting time of a process fault and to avoid misinterpretation of signals.

Lee and Liu (2012) proposed three new methods for utilizing joint information among response variables. These methods provide sparse estimators of the conditional inverse covariance matrix of the response vector, given explanatory variables as well as sparse estimators of regression parameters. They demonstrated with numerical examples that the proposed methods perform competitively in terms of prediction, variable selection, as well as inverse covariance matrix estimation. For short production runs, designing on-line SPC inspection activities can be difficult because of the lack of previous knowledge about the distributional properties of the quality characteristic to be monitored. To monitor the process mean in a short run, Celano*et al*. (2012) proposed the CUSUM t control chart and its economic design to overcome the problem of the preliminary estimation of the distribution parameters. Jaupi*et al*. (2013) statistical process control methods for monitoring short-run processes with multivariate measurements are considered and proposed techniques in general, and the influence functions may be used to build up to either nominal values or estimates & illustrated with real datasets, from a flexible job shop manufacturing system producing spare parts for classical cars.

The MSPC diagnosis is designed to interpret the result of MSPC. Because the MSPC only signals the occurrence of an out-of-control event; it does not provide further information about what are the problematic variable(s) and its contribution. Mason *et al*. (1997) discussed the problem of interpretation of signal in multivariate control charts. They suggested a procedure for decomposing the T^2 static into orthogonal component, which aids the interpretation effort. They also recommended a procedure for faster sequential computation scheme for decomposition. Principal component analysis is one of the techniques to analyze further.

2.3 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 (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 monitor an industrial process. PCA is formulated within a maximum-likelihood framework, based on a specific form of Gaussian latent variable model and discussed the advantages of this model in the context of clustering, density modelling and local dimensionality reduction, and demonstrated its application to image compression and handwritten digit recognition (Tipping and Bishop, 2009).

Bersimis*et et al.* (2007) discussed elaborately about the basic procedures for the implementation of multivariate statistical process control via control charting. Furthermore, they reviewed multivariate extensions for all kinds of Univariate control charts, such as multivariate Shewhart type control charts, multivariate CUSUM control charts and multivariate EWMA control charts. They also reviewed unique procedures for the construction of multivariate control charts, based on multivariate statistical techniques such as principal components analysis (PCA) and partial least squares (PLS).

D' Aspremont*et et al.* (2008) presented a new convex relaxation of sparse principal component analysis, and derived tractable sufficient conditions for optimality in machine learning and engineering applications. Mohamad-Saleh and Hoyle (2008) applied PCA technique for elimination of correlated data in the raw Electrical Capacitance Tomography (ECT) for oil fraction estimation from gas-oil flows.

Sutherland and Parente (2009) proposed a modeling approach based on PCA and tested a priori using direct numerical simulation data. They outlined a methodology for constructing a reduced model for the thermochemical state from high-fidelity data with particular focus on the ability to parameterize source terms appearing in the transport equations for the principal components.

Alexandru-Ionut*et et al*. (2012) attempted to introduce a methodology based on using PCA in conjunction with Geographical Information Systems (GIS) modeling to assess the level of development within the territorial subunits of a given region in Romania, with different sizes, tested the hypothesis according to which the level of development cannot be accurately described by variables looking at a single aspect (e.g., economic, social, cultural or environmental).

Zhang *et al.* (2010) proposed a spatially adaptive efficient image denoising scheme by using principal component analysis with local pixel grouping to improve quality of the image.

Yap *et al.* (2013) investigated the application of principal component analysis in the selection of financial ratios that are significant and representative for two industry sectors (i.e. consumer products and the trading and services sectors) in Malaysia.

There is a limited research in monitoring of complex processes in 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.

3. Methodology

To monitor the process, the methodology of T^2 generalized variance control chart is presented.

3.1 Principal component analysis

The practitioners should know what input variables need to be stable in order to achieve stable output, and then these variables are rightly monitored. The critical variable of the process may be identified by regression analysis. When the number of monitored variables is only 1 (N=1), then it is suggested to use USPC control charts more than 1 (N>=2), then it needs to be examined whether these variables correlate with each other. Correlation coefficient can be used as a criterion to decide the strength of the correlation between variables.

3.2 Control limits construction

It is important to purge the preliminary data to obtain an in-control data. The data purging includes identifying and removing outliers and/or substitute missing data with an estimate. This in-control data plus / minus three sigma is established as a norm to monitor the future observations and to see whether it significantly deviates away from the norm. The out-of-control observations were removed to monitor for future observations.

3.3 Monitoring of future observations

A period of future observation with specific number of observations will be analyzed with T^2 generalized control chart and see if any observation is out-of-control. The Hotelling'sT^2 generalized statistic is calculated for each new observation based on the mean and the covariance matrix obtained from the in-control data set. The control chart signals the out-of-control situation during the future observations. But it is not known which variable or set of variables is responsible for it. MSPC diagnosis is useful to identify those variables.

3.4 Diagnosis of critical variables

An out-of-control situation occurs while using USPC control charts, then the responsible variable(s) will reveal easily. While using T^2 control chart, the diagnosis of responsible variable(s) of an out-of-control situation will require more analysis. The contribution of each variable to the out-of-control observation can be determined using Principal Component Analysis.

4. Case Study

The production of hot metal is one of the most important and critical processes in steel making process. The blast furnace is the first step in producing “Hot Metal” from iron oxides subsequently sent to produce “Steel” at Steel Melt Shop. The first blast furnaces appeared in the 14th Century and produced one ton per day. Blast furnace equipment is in continuous evolution and modern, giant furnaces can produce 13,000 tons of hot metal per day. Even though equipment is improved and higher production rates can be achieved, the processes inside the blast furnace remain the same.

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 iron ore, coke and limestone are dumped through the top, and preheated air is blown through the bottom. The hot air that was blown into the bottom of the furnace ascends to the top after going through numerous chemical reactions. The raw materials require 6 to 8 hours to descend to the bottom of the furnace where they become the final product of liquid slag and hot metal and drained from the respective tap holes at regular intervals.

The inputs like sinter, coke are pre-processed before using in Blast Furnace. The hot air that was blown through the bottom of the furnace ascends to the top after going through numerous chemical reactions. This hot reducing gas travels up to the top of the furnace passing through the descending layers of ore and coke. Thus raw materials are heated up as they descend down through the furnace. When the burden material reaches temperatures over 1100 °C it starts to soften and completely melts at 1450 °C. This region of the furnace where softening and melting occurs is called the cohesive zone. The main chemical processes in a blast furnace are the combustion of the fuel and the reduction of iron, Sulphur, Silicon, Manganese, and other elements. Coke is consumed in reduction process along with the fuel blown in at the tuyeres, is burned. Gases with temperatures of 1600°-2300°C and containing 35–45 percent CO, 1–12 percent H_2, and 45–65 percent N_2 rise in the furnace and heat the descending charge, during which process the CO and H_2 are partially oxidized to CO_2 and H_2O. As a result, hot metal is produced in liquid form, reach the hearth where molten metal settles down at the bottom and slag floats on top and hot metal drained from the furnace.

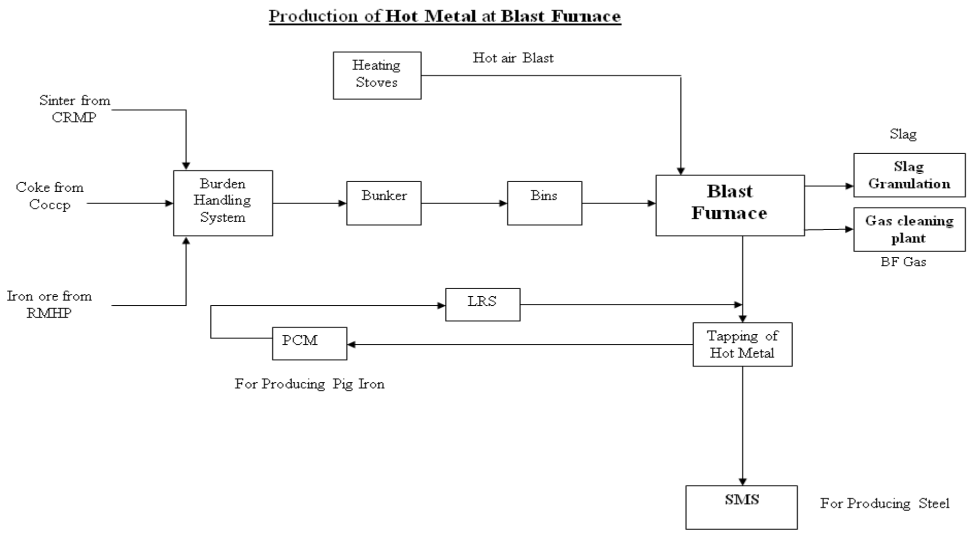

Figure 1. Process flow diagram of Hot Metal process in Blast Furnace

The process data is collected for 46 days and total of 370 observations were analyzed. 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 Consumption (M^3/hr.), Ash, Moisture, Volatile Material, Fe(%), FeO(%), SiO_2(%), Al_2O_3(%), CaO(%), MgO(%), Mn(%), SiO, Sulphur(S), Phosphorus(P), Manganese(Mn), Silica(Si), MnO(%) etc.,

The hot metal with lower silicon and sulphur contents is required for the production of quality Steel at Steel Melt Shop. For the production of quality hot metal, it is essential to identify and optimize raw materials quality, Blast Furnace operating conditions.To reduce abnormality of steel making at Steel Melt Shop (SMS), Blast Furnace is supposed to supply the hot metal in the following composition:

Silicon (Si) = 0.3 - 0.6%
Manganese (Mn) = 0.25% max
Phosphorous (P) = 0.15% max
Sulphur (S) = 0.04% max

5. Results and discussion

5.1 Process investigation and 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. Monitoring a large amount of variables is not efficient. Only the critical quality characteristics should be selected and monitored. The practitioners should know what input variables need to be kept stable in order to achieve stable output, and then these variables are appropriately monitored. The critical process variable of the process may be identified by Regression Analysis. The Regression analysis tool performs linear regression analysis by using the "least squares" method to fit a line through a set of observations. You 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.

Even if the variation in input variables were known, the exact reason was difficult to identify due to complexities in Blast Furnace Process. In order to understand the relationship between the input and output variables in the outgoing hot metal, the data is analyzed using regression analysis. In the analysis, each output composition is studied individually first to identify the process variables that would give the required composition of that output. Then, all the critical output variables are studied to find the process settings that would yield the desired compositions of all the constituents.

Accordingly regression analysis was performed with the help of MINI tab software based on output quality of hot metal and Blast Volume (m^3/min), Blast Pressure (Kg/cm^2), Blast Temperature (^0C), Steam (t/hr.), Oxygen Enrichment and Oxygen Consumption (m^3/hr.), SiO_2 (%) and CaO (%) are identified as critical process variables (p value < 0.05) to find out dependency and relationship between them, which may influence the quality of hot metal.

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. The correlations among the process variables are generated with the help of MINI tab, statistical software. Table 1 shows the correlation among the process variables generated from the data.

Table 1. Revealed characteristics and the three models of innovation

	Blast Pressure	Blast Volume	Blast Temperature	Oxygen Enrichment	Oxygen Consumption	Steam	SiO_2	CaO
Blast Pressure	1.000	0.981 (0.00)	0.506 0.000	0.441 (0.00)	0.462 (0.00)	0.630 (0.00)	-0.043 (0.407)	-0.259 (0.00)
Blast Volume		1.000	0.322 (0.00)	0.484 (0.00)	0.505 (0.00)	0.626 (0.00)	-0.024 (0.639)	-0.245 (0.00)
Blast Temperature			1.000	0.279 (0.00)	0.295 (0.00)	0.322 (0.00)	0.183 (0.00)	0.405 (0.00)
Oxygen Enrichment				1.000	0.991 (0.00)	0.587 (0.00)	0.039 (0.454)	0.405 (0.00)
Oxygen Consumption					1.000	0.608 (0.00)	0.052 (0.321)	-0.360 (0.00)
Steam						1.000	-0.140 (0.007)	-0.144 (0.005)
SiO_2							1.000	0.298 (0.00)
CaO								1.000

Note: The values shown in the brackets indicate ‘p’ values

From the Table 1, it is observed that there is a strong correlation between Blast Pressure and Blast Volume. There is a moderate positive correlation with Blast Temperature, Oxygen Enrichment, Oxygen Consumption & steam and weak negative correlation with CaO. Blast Volume shows moderate positive correlation with Blast Temperature, Oxygen Enrichment, Oxygen Consumption & Steam and weak negative correlation with CaO. Blast Temperature shows moderate positive correlation with Oxygen Enrichment, Oxygen Consumption & Steam and weak negative correlation with CaO. Oxygen Enrichment shows strong positive correlation with Oxygen Consumption and moderately with steam and CaO. Oxygen Consumption shows moderate positive correlation with steam, weak correlation with SiO_2 and negative correlation with CaO. Steam shows negative correlation with SiO_2 and CaO. SiO_2 has moderate correlation with CaO. Since the p-values are smaller than 0.01 indicates that there is sufficient evidence that the correlations are significant at 1% level.

5.2 Control limit construction

A set of data containing observations on 370 samples were 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 (Figure 2 to Figure 9).

$\bar{X}$Charts of Blast Pressure and Blast Volume are shown in Fig.2 and Fig.3 respectively. From the figures it is observed that the nine observations (354, 355, 356, 357, 358, 359, 360, 361 and 362) for both the variables fall outside the control limits, implying an unstable process. $\bar{X}$Charts of Blast Temperature, Steam, Oxygen Enrichment and Oxygen Consumption are shown in Fig.4 to Fig.7 respectively. From the figures it is observed that that the process is falling within the specification limits, implying a stable process.$\bar{X}$Chart of SiO_2 is shown in Fig.8 and from the figure it is observed that two of the observations (229 and 230) fall outside the control limits, implying an unstable process. It is also observed that $\bar{X}$Chart of CaO shown in Fig. 9 indicates that the process is falling within the specification limits, implying a stable process.

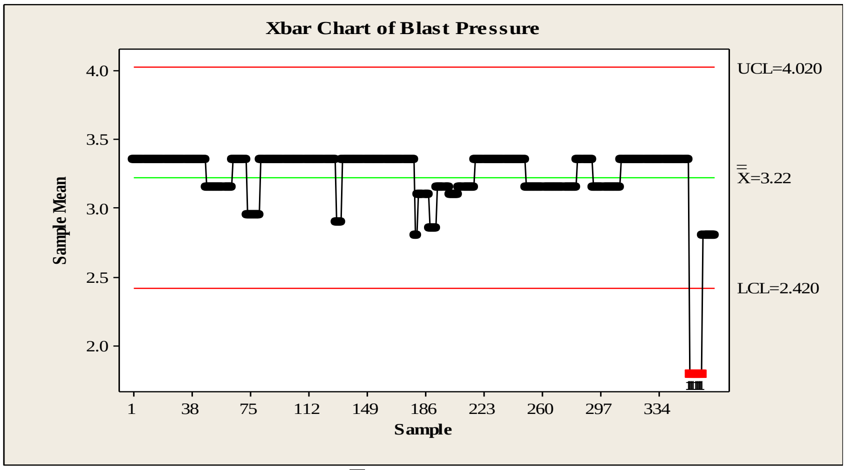

Figure 2. $\bar{X}$Chart ofBlast Pressure

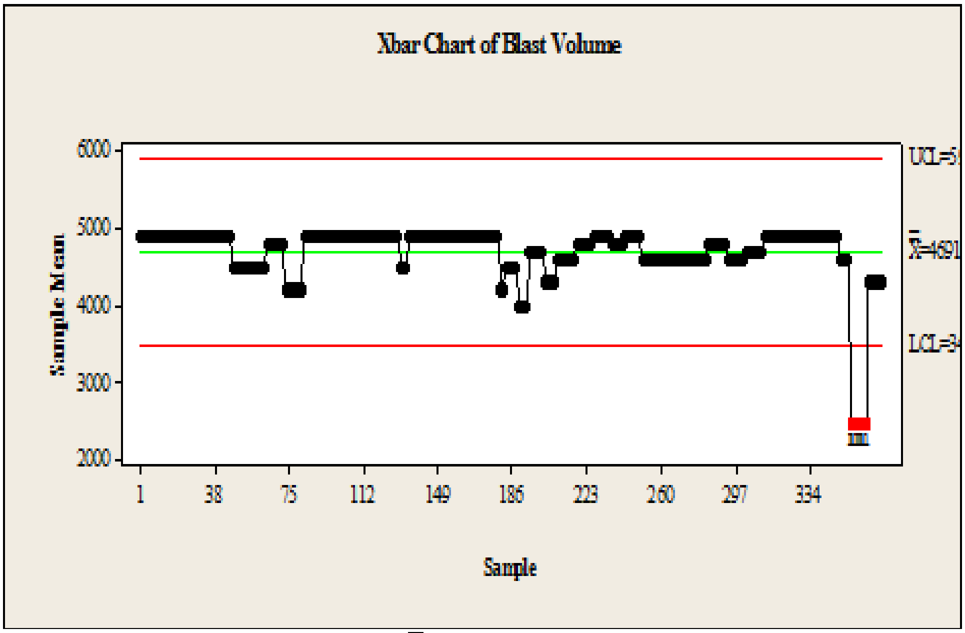

Figure 3. $\overline{X}$Chart ofBlast Volume

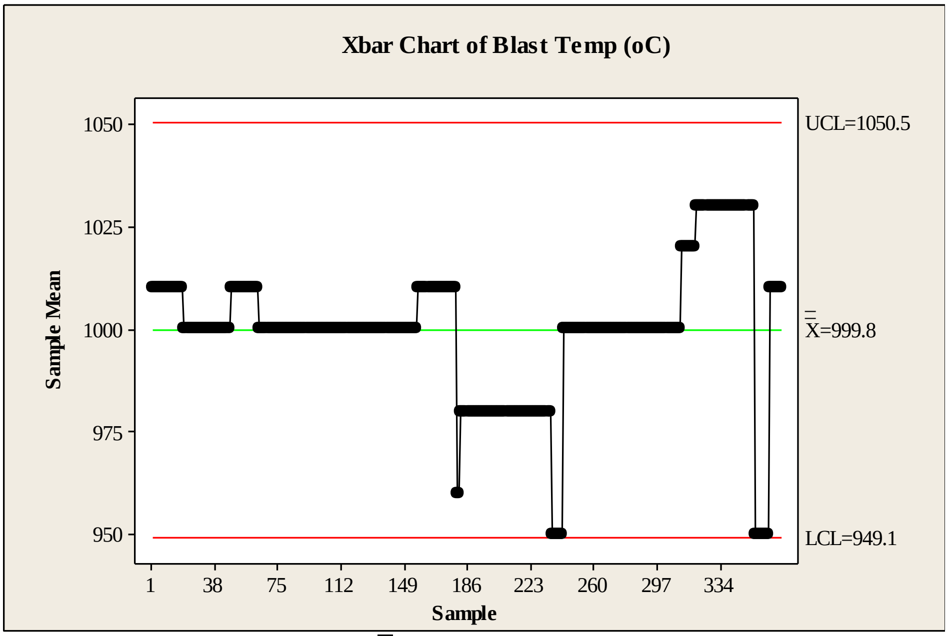

Figure 4. $\overline{X}$Chart ofBlast Temperature

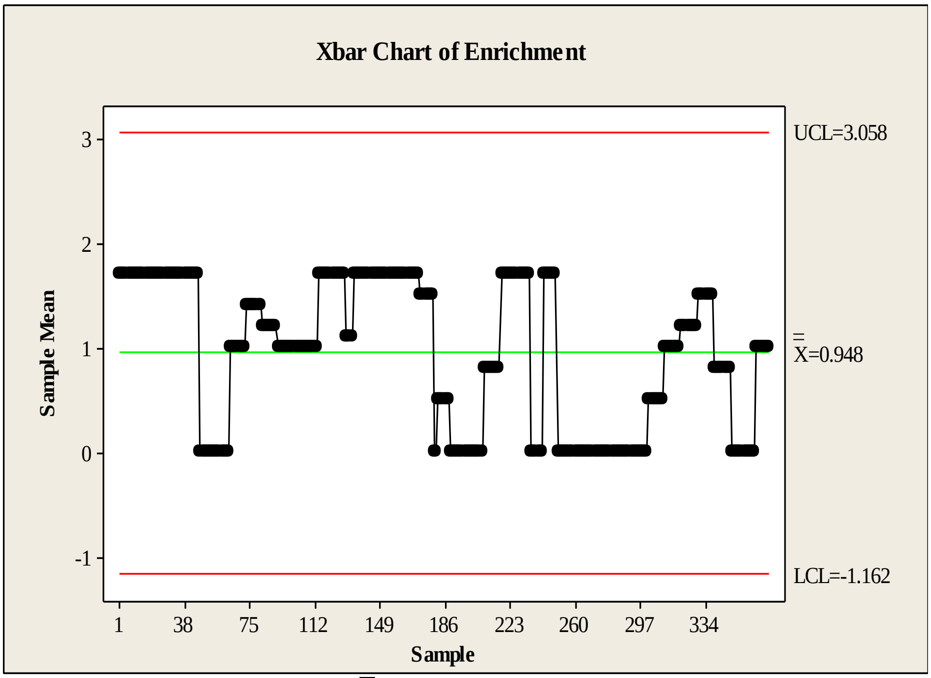

Figure 5. $\overline{X}$Chart ofOxygen Enrichment

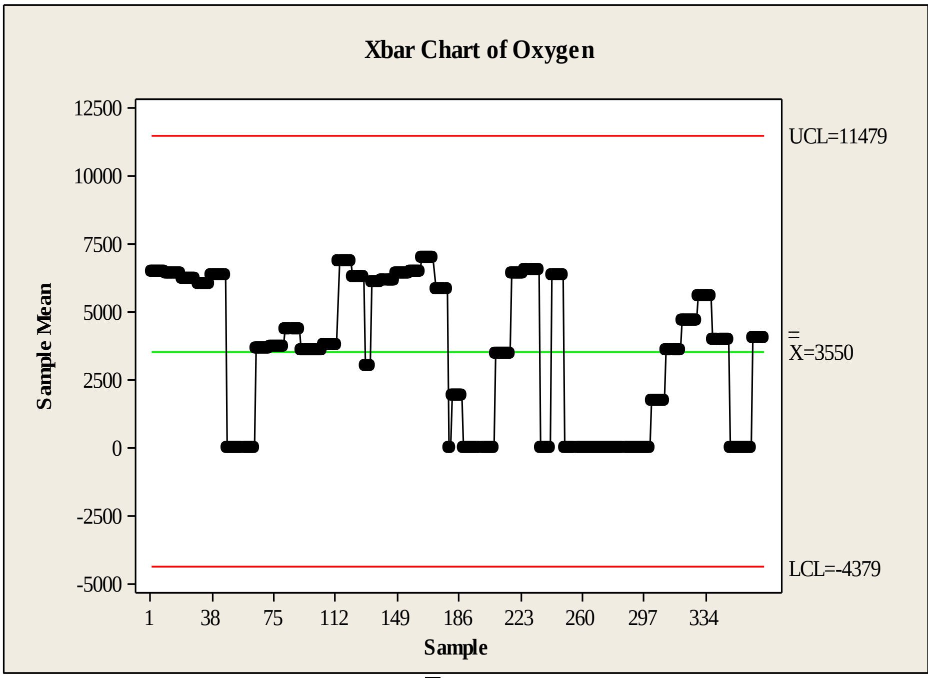

Figure 6. $\overline{X}$Chart ofOxygen

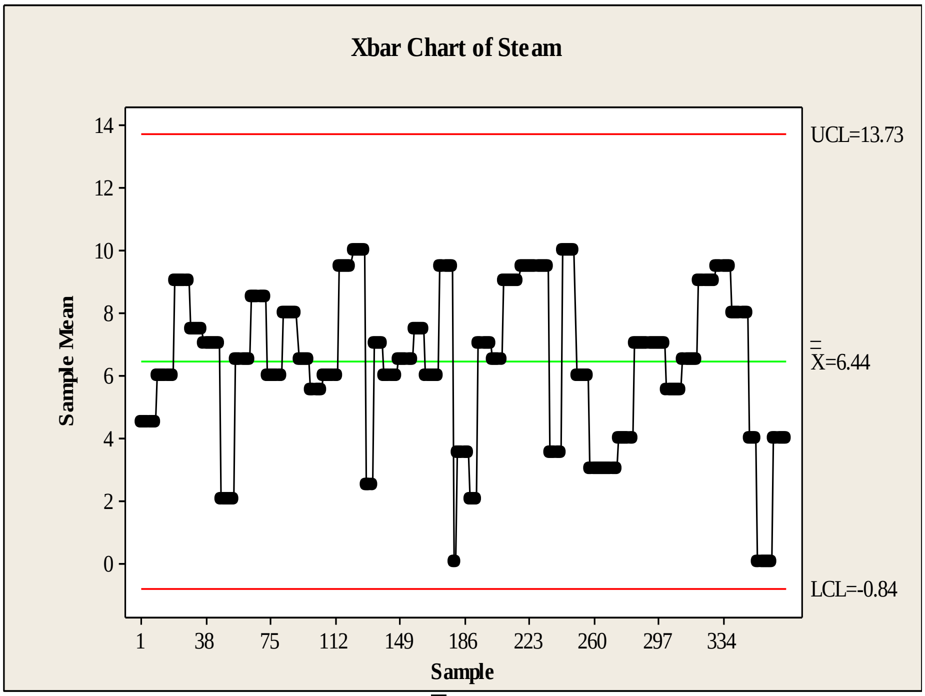

Figure 7. $\overline{X}$Chart ofSteam

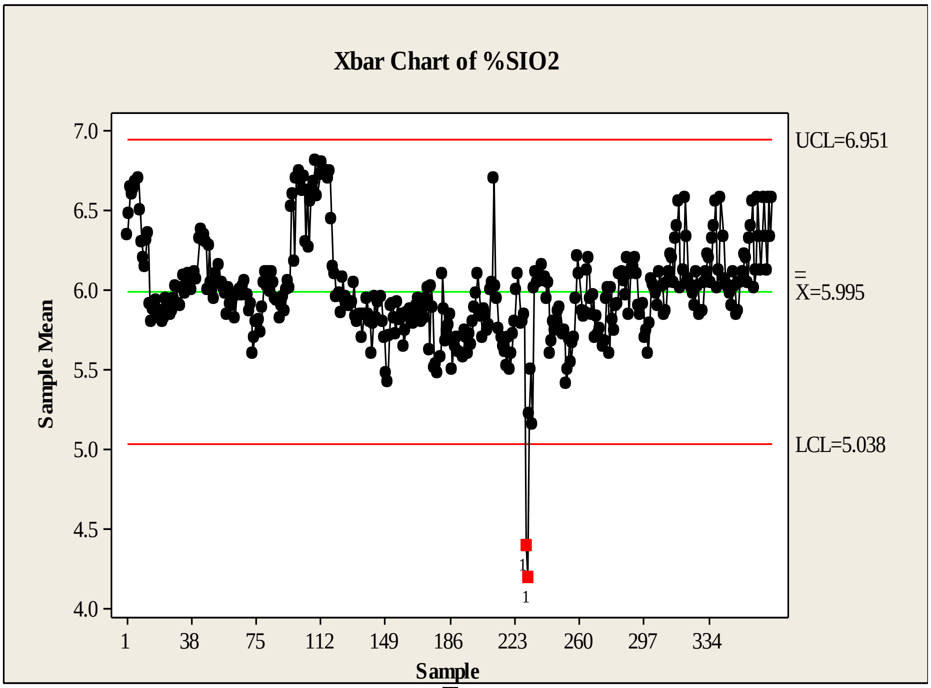

Figure 8. $\overline{X}$Chart ofSiO_2

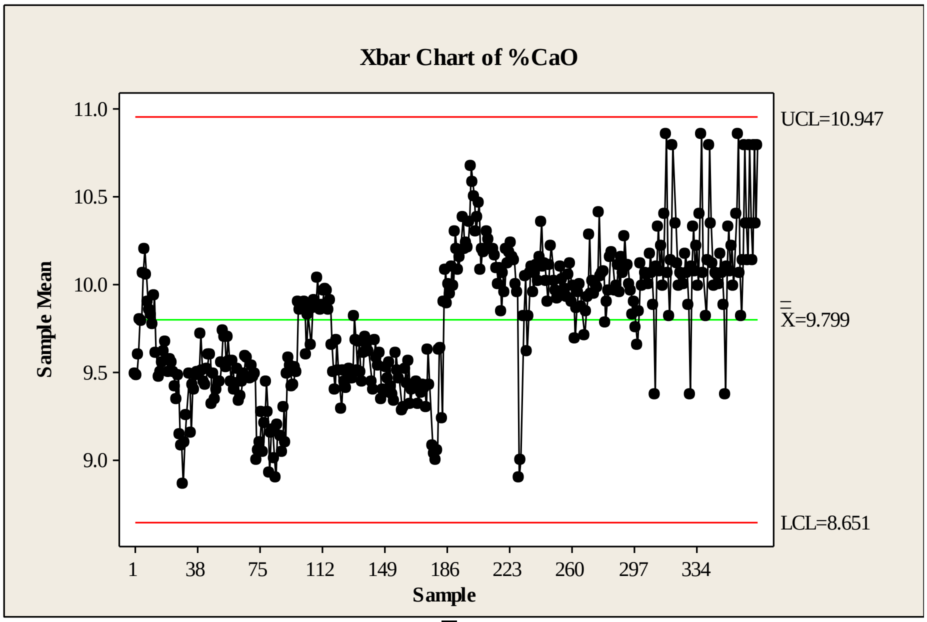

Figure 9. $\overline{X}$Chart ofCaO

These USPC control charts are necessary to identify the out-of-control observations and to establish norm to monitor the future observations.

5.2 Control Limit Construction

The T^2 control chart was also constructed (Fig. 10) to see whether any observation containing a problematic relationship between parameters. From the figure it is observed that the there is an indication of out-of-control of eleven observations (229, 230, 354 to 362) fall outside the control limits.

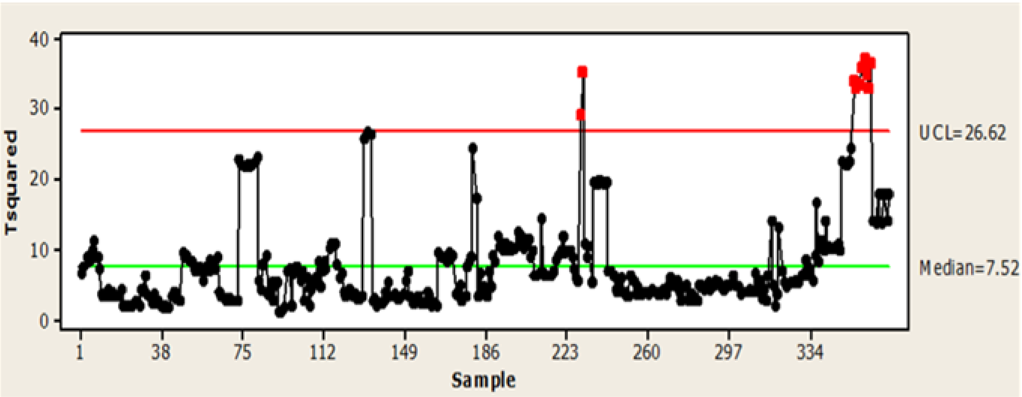

Figure 10. T^2 Generalized variance chart for critical process variables

Yet it is not known which variable or set of variables is responsible for out of control and PCA is adopted to identify contribution of each critical process variable.

6. Diagnosis of Responsible Variables

T^2 diagnosis is carried out with Principal Component Analysis. Principal component analysis is a variable reduction procedure. Normalized PCA scores are calculated to see which one(s) has/have higher scores. Fig.11 shows the chart of overall average contribution of each variable. The analysis indicates that the data are auto correlated. From figure 11, it is observed that SiO_2 (highest contribution of 0.6) causing out-of-control situation in observation number 359 and moderately in 229, 230, 356, 358, 360, 361 &362. There is a moderate contribution by Blast Volume causing out-of-control in observation number 229, 230 and Blast Pressure in observation number 354, 356, 358, 360 and 362. The impact of other critical process variables in the process is having very less impact.

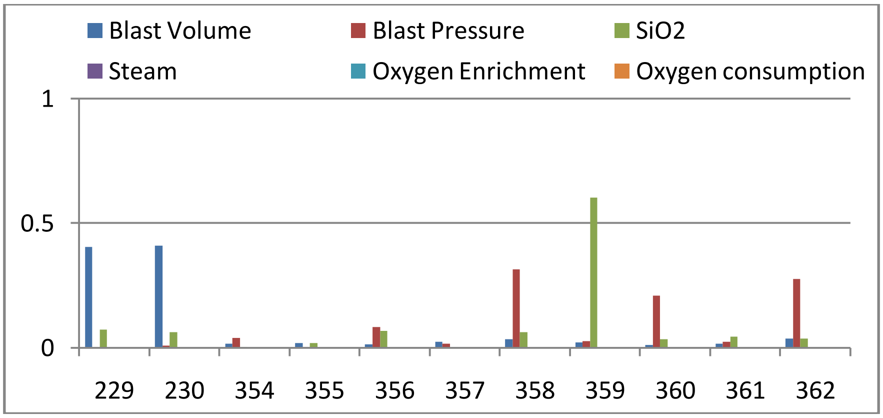

Figure 11. Overall average contribution of critical process variables.

Table 2. Diagnosis of critical process variables.

S.no.	Observation Number	Signaled by MSPC	Potential problematic variable(s)	Signaled by USPC
1	229	Out of control	Blast Volume SiO_2	In control Out of control
2	230	Out of control	Blast Volume SiO_2	In control Out of control
3	354	Out of control	Oxygen Enrichment Blast Pressure	In control Out of control
4	355	Out of control	Oxygen Enrichment SiO_2	In control In control
5	356	Out of control	Blast Pressure SiO_2	Out of control In control
6	357	Out of control	Oxygen Enrichment Blast Pressure	Out of control Out of control
7	358	Out of control	Blast Volume Blast Pressure	Out of control Out of control

S.no.	Observation Number	Signaled by MSPC	Potential problematic variable(s)	Signaled by USPC
			SiO_2	In control
8	359	Out of control	Blast Volume Blast Pressure SiO_2	Out of control Out of control In control
9	360	Out of control	Oxygen Enrichment Blast Pressure SiO_2	In control Out of control In control
10	361	Out of control	Oxygen Enrichment Blast Pressure SiO_2	In control Out of control In control
11	362	Out of control	Oxygen Enrichment Blast Pressure SiO_2	In control Out of control In control

Diagnosis of the out-of-control observations for potential process variables are shown in Table 2. From the Table 2 it is noticed that for 229 and 230 observations Blast Volume is signaled out-of-control in MSPC chart, the same was signaled in control in USPC chart. For the observations 358 and 359 Blast Volume is signaled out-of-control in both MSPC and USPC. SiO_2 is signaled out-of-control in MSPC charts for observations 229, 230, 355, 356,358 to 362 and the same is signaled in control for all observations except 229 and 230.

7. Conclusion

The control of dynamic behavior of process variables in a process has been challenging and often inexpressible in practice. Some industries use traditional statistical process control techniques which are not valid for monitoring the dynamic behavior. Others rely on experience and guesswork. 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 individual USPC chart for each variable. This paper explores problems in process monitoring variables in USPC. In some complex processes, when more number of variables is correlated with each other, monitoring simultaneously with MSPC charts having the problem of interpreting an out-of-control signal and detecting their contribution is difficult and needs further investigation. In such situations we recommend using principal components analysis for further analysis. The same technique is applied in this case study and reduce 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.Silica contribution into blast furnace needs control by suppression of SiO_2 generating. This can be achieved by maintaining consisting inputs of iron ore, coke, sinter and operating parameters of the furnace. The relationship among variables must be interpreted with caution. 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 the process of Blast furnace. The future research aimed is to apply the similar type control charts at Sinter Plant and Coke-ovens to supply the sinter and coke respectively at desired level of inputs to Blast furnace.

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