# A Nonlinear Monitoring Strategy for Blast Furnace Characteristics

Ashish Kumar, Anupam Das and Swarnambuj Suman



November 2, 2021

# A Nonlinear Monitoring Strategy for Blast Furnace Characteristics

Ashish Kumar[1[0000-0001-5477-7710]],Anupam Das[1#[0000-0002-0484-218X]] and Swarnambuj Suman[1[0000-0003-1538-4820]]

[1] National Institute of Technology Patna, Bihar, India 800005
[#]das.anupam13@gmail.com

**Abstract.** The article delves about the development of a Process Monitoring Strategy of the Blast Furnace of a Steel Making Shop (SMS). Blast Furnaces are employed for production of molten pig iron from sintered iron ore for subsequent production of plain or alloy carbon steel. Proper monitoring strategy of Blast Furnace assumes great importance owing to the fact that the quality of the molten pig iron thus produced has a bearing on the ultimate quality of the steel being produced by the concerned steel making plant. The Process Monitoring Strategy devised considered the nonlinear relationship existing amongst the process and feedstock characteristics associated with the Blast Furnace. The methodology being employed for development of the strategy is an amalgamation of Artificial Neural Network (ANN) and Principal Component Analysis (PCA) collectively termed as Neural Network Fitting-Principal Component Analysis (NNF-PCA) model. The ANN model was used for addressing the issue of nonlinearity by transforming the nonlinear process and feedstock characteristics observations of the Blast Furnace into its fully or partially linear counterpart and PCA was used for development of the nominal model for monitoring of the characteristics associated with the Blast Furnace. The monitoring of the Blast Furnace included detection of the fault by employment of PCA score based control chart and their subsequent diagnosis attained by the usage of appropriate fault diagnostic statistic.

Keywords: Process Monitoring Strategy, Blast Furnace, Artificial Neural Network, Principal Component Analysis, Control Chart, Fault Diagnostic Statistic.

## 1 Introduction

Blast furnace [1] can be referred as a metallurgical furnace engaged in the production of pig iron which is an integral part of Steel Making Shop (SMS) [2]. Working of blast furnace is based on the process of chemical reduction in which fuel (coke), flux (limestone) and sintered iron ore (collectively known as furnace charge) are supplied from the top and hot air also known as blast is supplied from the bottom of the blast furnace through a series of openings known as tuyeres. Downward flowing furnace charge reacts with upward flowing blast to produce molten metal and slag at the bottom and waste gases exit from the top of the furnace. The technology of blast furnace in steel making will continue to be used for years to come owing to its cost competiveness and efficiency with respect to size [3]. In order to improve the quality of steel being produced proper monitoring of the blast furnace characteristics of a steel making shop becomes an important aspect.

Multivariate projection based strategy such as strategies mainly based on Principal Component Analysis (PCA) [4-5] and Partial Least Squares Regression (PLSR) [6] have been widely used for the development of monitoring strategy. These are based on the assumption of linear relationship amongst the characteristics and are used in order to avoid the computational complexity associated with nonlinear techniques. Furthermore application of linear techniques to nonlinear problem may give rise to erroneous results. In recent decades, development of various nonlinear counterparts of the linear techniques of process monitoring has been observed. Nonlinear techniques of process monitoring can be broadly divided into three major categories viz. linear approximation based technique, Kernel function based techniques and artificial intelligence (AI) based techniques. Bayesian inference [7] comes under the linear approximation based technique of process monitoring in which a nonlinear space is approximated by several linear sub-spaces and separate monitoring strategy needs to devise for each sub-space which is further amalgamated using Bayesian inferences. Kernel function based strategy such as Kernel principal Component Analysis (KPCA) [8] and Kernel Partial Least Squares regression (KPLSR) [9] involves mapping the nonlinear space to high dimension feature space using kernel functions such as Gaussian kernel function or radial basis function to high dimension feature space where data behaves more linearly and PCs are extracted through the eigen decomposition of the covariance matrix of the feature space. AI [10] based techniques such ANN [11-12] and Fuzzy Logic [13] has also found profound application in nonlinear process monitoring is comprised of development of a neural network which learns the nonlinear relationships amongst the characteristics and transforms it to partially or fully linear through minimization of reconstruction error.

In this article a process monitoring strategy has been developed to monitor the process and feedstock characteristics associated with the blast furnace of an SMS considering the high dimensionality and nonlinear relationship amongst the characteristics. NNF-PCA which is an amalgamation of ANN and PCA has been employed for the development of the nominal model and fault detection has been achieved through the employment of score based Hotelling $T^2$ chart [14]. Furthermore fault diagnosis has been carried out by suitable fault diagnostic statistic preferably contribution plot [14]. The paper has been organized or structured in the following manner viz. introduction of process monitoring and brief review about the nonlinear process monitoring strategy, description of NNF-PCA approach of process monitoring technique with their mathematical details, case study pertaining to the SMS, analysis and conclusions.

## 2 NNF-PCA working

NNF model comes under the non supervised ANN which is an AI based technique of process monitoring. In NNF model the nonlinear data set is transformed to partially or fully linear through the development of a neural network (by appropriately selecting activation function, weight and bias vector) and minimizing the reconstruction error. The developed neural network consisted of three layers viz. input layer, hidden layer and output layer. Transformation from input layer to hidden layer is encoding while transformation from hidden layer to output layer is decoding. A nonlinear encoding

with linear decoding transforms the nonlinear data set to partially or fully linear form. The mathematical details of the NNF model is provided below
The input data in the form of matrix X is fed to the input layer which gets transformed to Z (latent code or latent representation) as represented in equation 1

$$Z = \alpha(x) \triangleq \sigma(WX + b) \qquad 1$$

Where $\alpha$ is the nonlinear transformation function, σ(.) is an activation function like sigmoid function, matrix W is parameter matrix which tells about the weight associated with each input and b is a biased vector.
The latent code or latent representation Z can further be transformed into output $\tilde{X}$ which can be mathematically represented as

$$\tilde{X} \ = \ \beta(Z) \ = \tilde{\sigma}(\tilde{W}Z + \tilde{b}) \qquad 2$$

Where$\sigma$, $\tilde{X}$ and $\tilde{b}$ of decoder part may be different from encoder part and β is nonlinear transformation function. In order to learn the parameters in the activation function the neural network is trained to minimize the reconstruction error.

$$[W,b; \tilde{W}, \tilde{b}] = \mathrm{argmin}\sum_{i=1}^{N} \|X\text{-}\tilde{\sigma}(\tilde{W}\sigma(WX+b)+b^2)\|^2 \qquad 3$$

After the transformation, PCA has been adopted for the extraction of features such as scores and loadings

# 3 Case Setting

The case under consideration is a Steel Making Shop (SMS) engaged in the production of steel ingots, situated in eastern India with production capacity of 0.5 million tons per annum. The SMS under consideration has following major stations viz. Coke Oven, Sintering Plant, Blast Furnace, Ladle Refining Furnace (LRF) and Continuous Casting Machine (CCM). Figure 1 depicts the flow chart of the SMS.

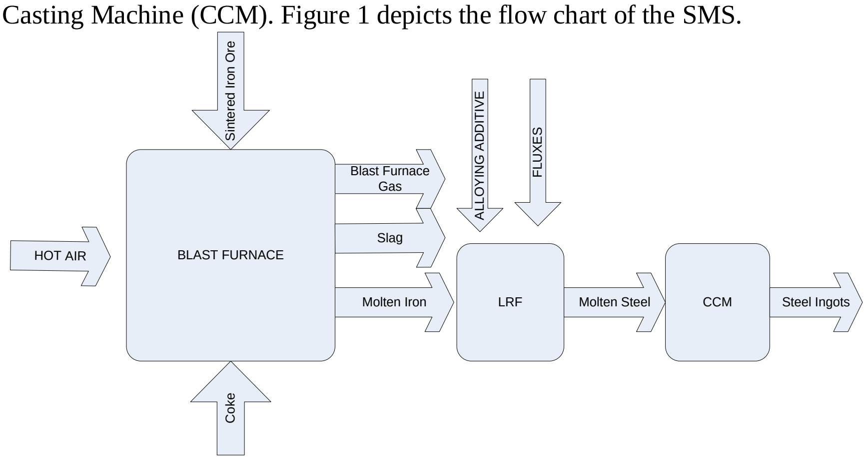

Fig 1: Flow chart of the SMS

Total of seven process and feedstock characteristics associated with the blast furnace of the SMS has been taken for the analysis. Table 1 depicts the process and feedstock characteristics associated with the blast furnace along with the descriptions and abbreviations.

Table 1: Process and feedstock characteristics details pertaining to Blast Furnace

| **Characteristics associated with Blast Furnace** | **Description** | **Abbreviation** |
|---|---|---|
| **Blast Temperature** | **Temperature of blast furnace in degree Celsius** | **BFT** |
| **Blast Rate** | **Rate of hot air supplied in $m^3$/sec** | **BFR** |
| **Skip Coke** | **Percentage of Coke with grain size 40-80 mm** | **BSC** |
| **Nut Coke** | **Percentage of Coke with grain size 10-40 mm** | **BNC** |
| **CD coal** | **Percentage of Coal Dust with grain size < 0.071 mm** | **BCD** |
| **Fe input from sintering plant** | **Percentage of Sintered Iron ore** | **BFE** |
| **CaO input** | **Percentage of Calcium Oxide** | **BCG** |

## 4 Analysis

In this article a nonlinear process monitoring strategy has been developed to monitor the process and feedstock characteristics associated with the Blast Furnace of the SMS that has been discussed in the previous section. To total of 90 observations of 7 process and feedstock characteristics associated or pertaining to the Blast Furnace has been considered for the analysis. The monitoring strategy has been developed considering the effect of nonlinear relationship amongst the characteristics as well as high dimensionality of the data set. The analysis has been carried out in five phases viz. Data Pretreatment, Data Pre-Processing, Model Development, Fault Detection and Fault Diagnosis.

Data pretreatment includes removal of outliers from the data as well as standardization of the data. Hotelling $T^2$ chart for individual observation has been adopted for the removal of outliers, no outliers have been found in the data set. Furthermore the data has been standardized using the general standardization formula to bring them in one scale. In Data pre-processing the nonlinearity testing and collinearity testing of the data has been carried out. Nonlinearity testing has been carried out by constructing fitted line plot between any pair of variables and obtaining their $R^2$ value (model fit value). $R^2$ value for any given pair of process and feedstock characteristics is found to be in the range of 0.6 to 1.2 which is an indicative of nonlinear relationship amongst the characteristics. Furthermore the collinearity testing has been accomplished by using Spearman's rank correlation analysis. Mathematical details of Spearman's rank correlation is provided in equation 9

$$\text{Spearman's rank correlation coefficient } (r_{s)} = 1 - \frac{6\sum_{i=1}^{n} di^2}{n(n^2-1)} \qquad 9$$

Where'd' is the difference between the ranked values and 'n' is the number of observations. The correlation coefficient amongst the characteristics is shown in table 2 is indicative of existence of appreciable correlations amongst the characteristics.

Table 2: Correlation coefficients of the characteristics associated with the Blast Furnace

| | BFT | BFR | BSC | BNC | BCD | BFE |
|---|---|---|---|---|---|---|
| BFR | 0.80 | | | | | |
| BSC | 0.91 | 0.20 | | | | |
| BNC | 0.82 | 0.86 | 0.70 | | | |
| BCD | 0.65 | 0.77 | 0.81 | 0.61 | | |
| BFE | 0.55 | 0.58 | 0.69 | 0.78 | 0.75 | |
| BCG | 0.84 | 0.68 | 0.20 | 0.41 | 0.40 | 0.66 |

The pretreated and pre-processed data has been used for the development of the nominal model. NNF-PCA has been adopted for the development of the nominal model which is an amalgamation of NNF model and PCA. NNF model comes under the ANN based technique of nonlinear process monitoring which involves transforming the nonlinear data set to partially or fully linear using a neural network. The neural network in this case consists of three layers viz. input layer with n nodes, hidden layer with p nodes ($p<n$) and output layer with n nodes. Appropriate activation function, weight and bias has been assigned for the network and transformation has been carried out through minimization of reconstruction error. After 3 iterations nonlinearity testing is further carried out using fitted line plot as discussed earlier, the $R^2$ value thus obtained lies in the range of 0.67 to 0.72 which indicate that data set has been transformed to partially linear form. For extraction of parameters such as scores and loadings PCA has been adopted. Figure 2 shows the Scree plot of the PCA and table X is showing the number of component along with their respective variance and cumulative variance.

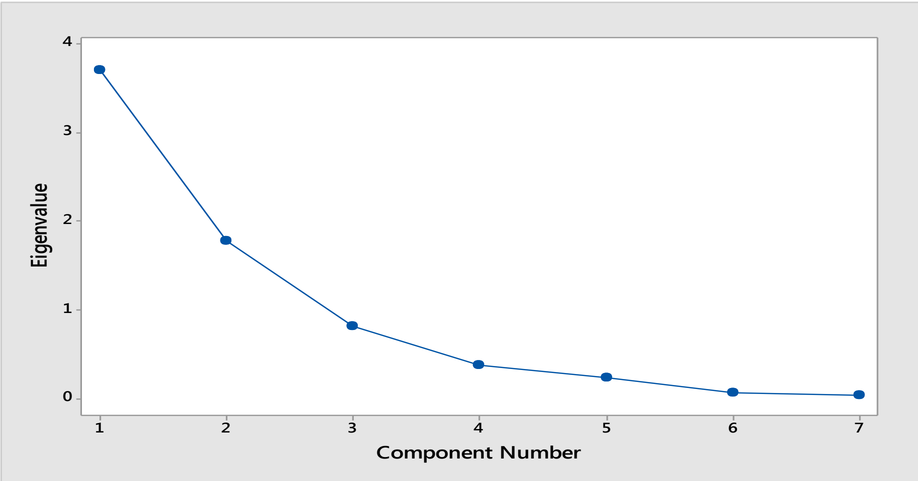


Figure 2: Scree plot of the PCA

Table 3: Variance and Cumulative Variance of the PCA

| **Component** | **Variance** | **Cumulative Variance** |
|---|---|---|
| **1** | **0.530** | **0.530** |
| **2** | **0.254** | **0.784** |
| **3** | **0.116** | **0.900** |
| **4** | **0.053** | **0.953** |

After model building, fault detection has been carried out. Multivariate control chart, Hotelling $T^2$ chart has been adopted for the detection of faults. Control limit has been established using 90 observations and remaining 30 observations has been treated as new observation. $T^2$ statistic of new observations has been plotted against the established control limit. Observation number 6 has been found as out of control observations. Hotelling $T^2$ chart for new observation is depicted in figure 3

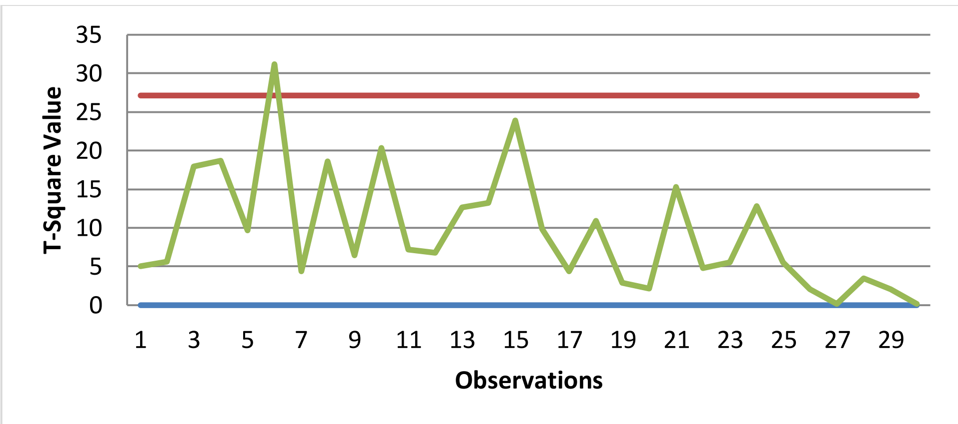

Figure 3: Hotelling $T^2$ chart for new observations

After the detection of fault next objective is diagnosis of the detected fault. It is associated with identifying the root cause of the fault. Contribution plot has been adopted for fault diagnosis, which shows the relative contribution of the characteristics towards the fault. Figure 5 depicts the contribution plot of the process and feedstock characteristics associated with the blast furnace. It is evident from the contribution plot that characteristic BFT is the major contributor towards the fault.

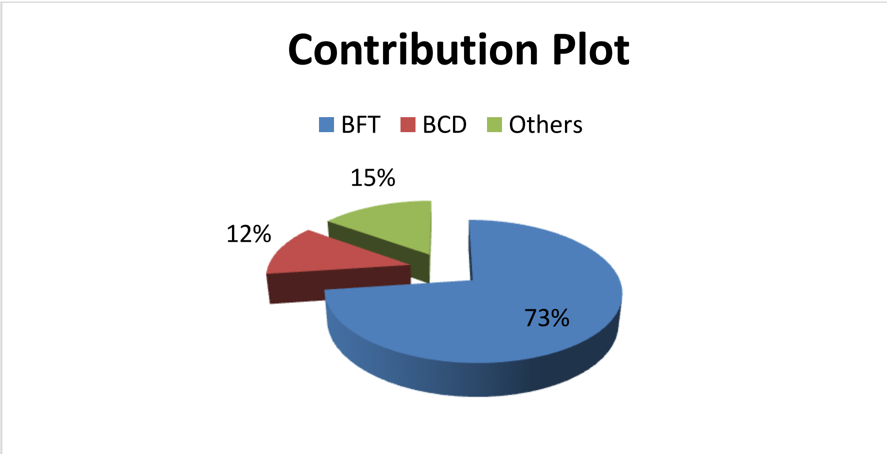


Figure 5: contribution plot for out-of-control observation no 6

## 5 Conclusions

A nonlinear process monitoring strategy was devised for monitoring of Blast Furnace characteristics of a SMS. A total of seven characteristics were considered. The nonlinear profiles of the measured characteristics were converted to its linear counterpart by employment of NNF model which removed the nonlinearity in the observations pertaining to the characteristics to a great extent. Thereafter the linear variant of the PCA was applied on the linearly transformed data for building of the process representation. For detection of the faults, Hotelling $T^2$ chart based on PCA scores was employed which detected one out-of-control observation of a total of sixty observations that were monitored. Contribution plot were constructed for determination of root causes also termed as fault diagnosis for the detected faults. The contribution plot for fault diagnosis depicted the relative contribution of the individual characteristics to the detected fault. For out-of-control observation no. 6, characteristic BFT's relative contribution to the detected fault was around 73%. Thus in the hindsight it can be assumed that the nonlinear process monitoring strategy thus devised was able to monitor the characteristics associated with the blast furnace in an efficient manner.

**References**

[1] Zhou, B., Ye, H., Zhang, H., & Li, M.: Process monitoring of iron-making process in a blast furnace with PCA-based methods. Control Engineering Practice, 47, 1–14 (2016).

[2] Tupkary, R.H. and. Tupkary, V.R.: An Introduction to Modern Steel Making, 6th edition, New Delhi: Khanna Publishers (1998)

[3] American Iron and Steel Institute.: How a Blast Furnace Works (2005).

[4] J, Cent.: PCA and LDA and its application to induction motor. South Univ. Technol. 17, 1238−1242 (2010).

[5] Xie, Y.; Wang, J.; Liang, Y.; Sun, L.: Robust principal component analysis by projection pursuit. J. Chemom. 7, 527− 541 (1993).

[6] Li, S., Ng, T.-T., & Yao, Z.-P.: Quantitative Analysis of Blended Oils by Matrix-assisted Laser Desorption/Ionization Mass Spectrometry and Partial Least Squares Regression. Food Chemistry, 127601(2020).

[7] Jiang, Q., Huang, B.: Distributed monitoring for large-scale processes based on multivariate statistical analysis and Bayesian method. Journal of Process Control, 46, 75-83(2016).

[8] Shang, J.; Chen, M.; Ji, H.; Zhou, D.: Recursive transformed component statistical analysis for incipient fault detection. Automatica. 80, 313−327 (2017).

[9] Si, Y.; Wang, Y.; Zhou, D.: Key-Performance-Indicator-Related Process monitoring based on improved Kernel partial least squares. IEEE Trans. Ind. Electron. (2020)

[10] Liu, J.; Chang, H.; Hsu, T.; Ruan, X.: Prediction of the flow stress of high-speed steel during hot deformation using a BP artificial neural network. J. Mater. Process. Technol. 103, 200− 205 (2000)

[11] Zhang, Q.; Liu, S.: Urban traffic flow prediction model based on BP artificial neural network in Beijing area. J. Discrete Math. Sci. Cryptography. 21, 849−858 (2018).

[12] Li, N.; Tuo, J.; Wang, Y.: Wang, M. Prediction of blood glucose concentration for type 1 diabetes based on echo state networks embedded with incremental learning. Neurocomputing 378, 248−259 (2020).

[13] Zhang, T., Xia, D., Tang, H., Yang, X., & Li, H.: Classification of steel samples by laser-induced breakdown spectroscopy and random forest. Chemometrics and Intelligent Laboratory Systems, 157, 196-201(2016).

[14] Suman, S., Das, A.: Stratified statistical monitoring strategy for a multi-product manufacturing facility with early detection approach. Computers & Industrial Engineering, 130, 551–564 (2019).