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# NOVEL APPROACH OF DATA RECONCILIATION IN CEMENT MILL FOR KERNEL PCR ALGORITHM

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**ABSTRACT**

The quality of finished product of a cement mill is measured in terms of blaine, which is the measure of specific area of cement. Normally blaine is measured offline and maintaining the blaine is very important because it directly hampers the cement strength and also affects production cost. A soft sensor based kernel autoregressive exogenous model (ARX) was developed to predict the blaine quality for a defined sampling period to be used in a controller. ARX model includes the past blaine predictions as regressors in addition to the other informative variables in order to predict the blaine. The quality of predictions is largely dependent on data; the construction of data to be used in the algorithm requires good process understanding as the raw data collected from the process will have many information that can mislead the prediction. This means the information may cause over fitting or sometimes reverse modeling because of excess information. In this paper, an automatic method to align data based on the process characteristics to be fed into the algorithm for improving the prediction based on data reconciliation method is proposed. Data Reconciliation (DR) is a technology that uses process information (input data's) and mathematical model to automatically align the variables according to the dynamics of the industrial processes.

**Keywords:** cement mill, blaine, KPCR, data reconciliation.

## 1. INTRODUCTION

Cement is a material that is capable of bonding materials such as building stones, bricks, sand, etc. The strength of cement depends on fineness and the measure of fineness or the specific surface area of cement is technically termed as Blaine. The clinker, gypsum and other additives (depending on the quality of cement) are grind together in cement mill. The quality of finished product from the cement mill is measured in terms of blaine.

Blaine is measured offline in hourly basis by collecting the final product samples using a sampler and analyzed in the quality lab [1]. The air permeability method is used to determine the fineness of the cement by measuring the resistance of flow of air over a compact cement surface. Based on the lab results process parameters are manipulated. So prediction of blaine based on process parameters will help in better manipulation of the process that will help to achieve good production with desired quality.

Raw materials are fed into the cement mill as a fresh feed, due to presence of different diameters of ball direct or cataract action occurs, which help the clinker and other additives to grind together into a fine material. The measure of sound level due to the cataract action is referred as folafone; main motor will be getting load variance due to changes in the fresh feed. The fine material at the output is carried to the separator via bucket elevators, based on separator speed finest material is extracted as final product where as coarse material are fed back into the cement mill as rejects. The schematic diagram and process flow of cement mill is shown in Figure-1.

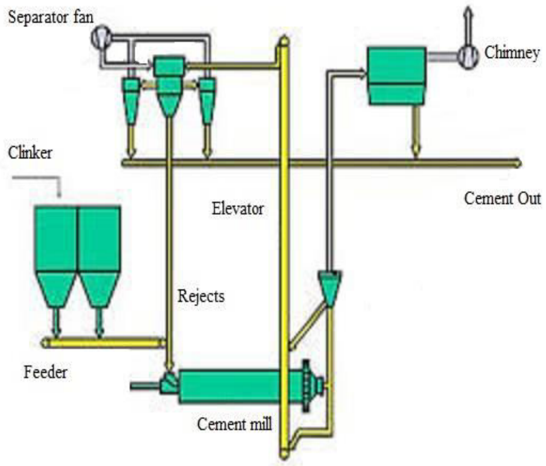


**Figure-1.** Schematic diagram and process flow of cement mill.

Principal component analysis (PCA) is a dimension reduction technique that also tries to identify the subspace where the data approximately lies. PCA utilizes the prior information of the process, taken it in the form of informative training data; this training data set is fed to a PCA model in order to recover the desired response of the process [2]. PCA is a powerful linear method for feature extraction which is known for its applications such as intrusion detection, face recognition, data compression, pattern recognition, process monitoring and so on.

The PCA and KPCA are distinct in the aspect that PCA being a linear method can only conserve the second order statistics of original data, thus PCA is not efficient for multiple feature of the pattern [3] [4]. On the other

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hand KPCA is nonlinear method where kernel transformation is used. In KPCA kernel mapping takes place, the data after mapping will be a high dimension space so it becomes difficult to extract the principal features. Therefore PCA and Kernel functions are used together in order to develop an efficient reliable system [5].

Soft sensing is a data driven method, thus for predicting the blaine of a cement mill real time historical data are used [6]. The real time data are used as regressors which are fresh feed, folafone, main mill load, bucket elevator load, separator speed and the rejects and the past blaine as well as its predictions. The past blaine data along with regressors are considered to get the better predictions because if only information variables are taken alone to predict the blaine then the regressors do not count for uncertainties in the model and hence the past values of blaine can help to improve the predictions.

The proposed article has implemented KPCR for predicting the blaine quality every minute by considering all the aforementioned regressors. We have also designed a novel approach of data reconciliation for auto updating and aligning the data which is to be fed into the algorithm. The preprocessing, automating and alignment of data gives promising predictions.

The introduction about the cement mill, blaine and methodology along with few literatures is discussed in Section 1. Section 2 gives an idea of the proposed algorithms and the simulation results. The data reconciliation and its advantage are discussed in Section 3. In Section 4 the conclusion and application is discussed.

## 2. MODELLING

The approach to develop the Kernel Principal Component Regression Algorithm is discussed briefly and the simulation results of blaine prediction is shown and discussed.

### 2.1 Principal component analysis

Suppose we have a data set $\{X^{(i)}, i = 1, \ldots\ldots, M\}$ of M different attributes. Before training the data we need to preprocess the data in order to normalize its mean and the variance in such a way that the mean should be zero and variance should be unity in order to rescale the different attributes on the same scale. Once the data is normalized we need to find the unit vector 'u' such that when the data when projected onto 'u' gives the maximum variance.

Now, we try to automatically find the direction 'u' such that the length of projection of data $X^{(i)}$ onto vector 'u' is '$X^T$u' which is at same distance '$X^T$u' from the origin so, we have chosen unit length 'u' to maximize the variance of the projection. Thus maximizing the variance gives the principal Eigen vector of the covariance matrix 'Ê'.

$$`\hat{E} = u^T \frac{1}{M} \sum_{i=1}^{M} X^{(i)} . X^{(i)^T} . u \quad (1)$$

We have chosen 'u' as the eigen vector of covariance matrix $\hat{E}$ if we want to find in its dimensional space to approximate the data, for projecting the data into a subspace we choose $u_{1, \ldots\ldots, } u_{k,}$ as the eigen vector of the covariance matrix [7]. Thus, $u_{1, \ldots,} u_k$ will form a new orthogonal basis for the data. In order to include $X^{(i)}$ in this new orthogonal basis we need to find corresponding vector '$Y^{(i)}$', such that

$$Y^{(i)} = [u_1^T X^{(i)} \ldots\ldots\ldots . u_k^T X^{(i)}]^T \in R^k \quad (2)$$

where $Y^{(i)}$ gives a lower dimensional representation for $X^{(i)}$. PCA is also known as dimension reduction algorithm [4] and the principal components of the data are the vectors $u_1, \ldots, u_k$. Thus PCA have been used to form a linear model between the explanatory variables and the output of interest that is the blaine.

### 2.2 Kernel principal component regression

Kernel PCA is an algorithm which is used to identify the pattern and preserves only the subspace that contains these patterns. It does it so by mapping the original space (R) with the feature space (F) using a nonlinear mapping function. The linear relations between the data points in the original space can be converted to non linear relation in the original space. The data point $X^{(i)}$ in the original space is represented as f($X^{(i)}$) in feature space. The relative distance between all the data points is given using Kernel matrix ($K_{ij}$) which is the inner product of all data points in feature space. $K_{ij}$ is a symmetric and positive semi definite [8], [9].

The elements of $K_{ij}$ are calculated using Kernel function,

$$K_{ij} = f(X^{(i)})\, f(X^{(j)}) \quad (3)$$

$$f(X^{(i)})\, f(X^{(j)}) = \exp - \|X^{(i)} - X^{(j)}\|^2 \quad (4)$$

### 2.3 Kernel principal component regression algorithm

In PCA dependent and independent variables are included in the same regression matrix where as in Principal Component Regression (PCR) only independent variables alone are treated as regressors. Another advantage of using PCR is it can overcome the problem of multi-co linearity by omitting some of the low variance principal components. KPCR model was developed using the training data obtained from FL Smidth Automation's CEMULATOR. Pseudo Random Binary Sequence (PRBS) signal has been used for collecting the data according to the sampling time of PRBS signal as shown in Figure-2.

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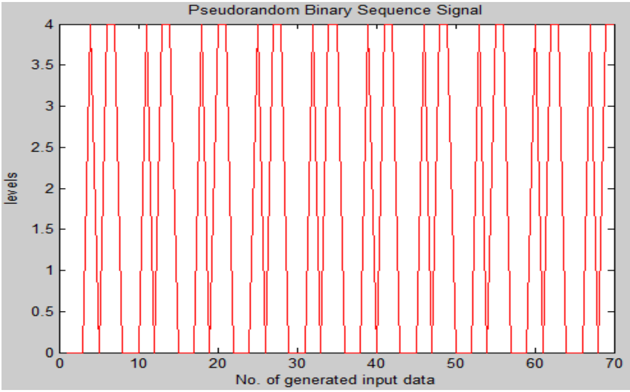


**Figure-2.** PRBS signal used for collecting data.

The part of simulated data obtained from the CEMULATOR is used for developing the model and rest part is used for validating the model. The training data includes all the regressors along with the past blaine predictions for precise predictions. The time trend of all the regressors and blaine due to change in feed for simulated data is shown in Figures 3 and 4.

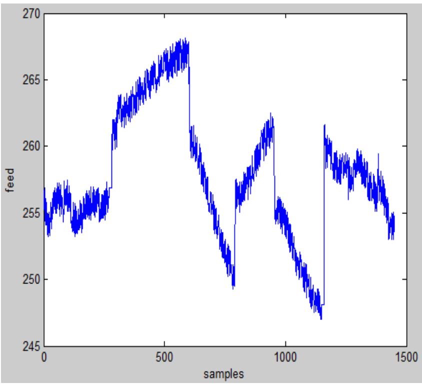


**Figure-3(a).** Feed.

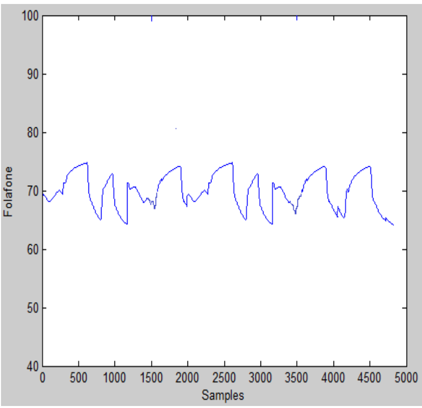


**Figure-3(b).** Folafone.

Considering all the explanatory variable for predicting the blaine, taking into account the delay between each explanatory variable and blaine and the dynamics of each explanatory variable, the regressor matrix is listed.

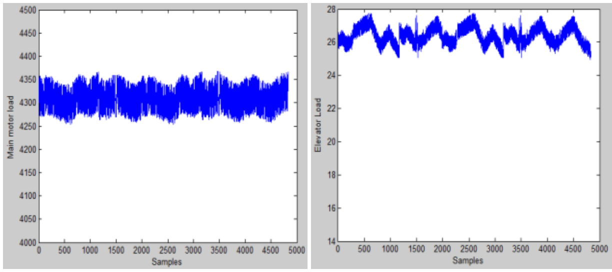

**Figure-3.** **(c)** Main motor load. **(d).** Elevator load.

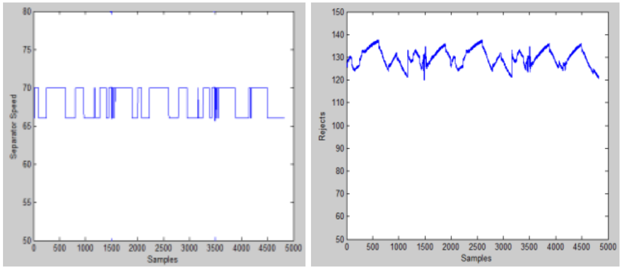

**Figure-3.** **(e).** Separator speed **(f).** Rejects.

**Figure-3.** Time trends of all the regressors due to the change in feed for simulate data.

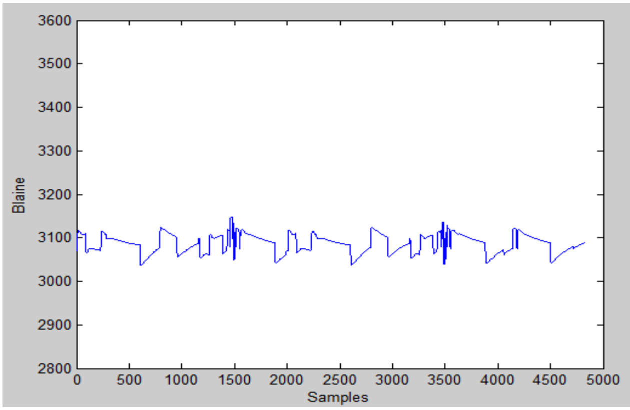


**Figure-4.** Time trend of Blaine due to the change in feed rate for simulated data.

The regressor matrix thus formed are transformed to a high dimensional feature space 'F' to extract non linear- ties, Gaussian Kernel with width σ is used whose feature space is infinite dimensional.

$$K(x(i), x(j)) = \exp-\|x(i) - x(j)\|/\sigma \quad (5)$$

The eigen values λ and the eigen vectors V are calculated from the covariance matrix (Kernel matrix K). Nonlinear model between the dependent and the independent variable is given by a linear model y between dependent variable and the variable in the feature space.

$$y = B\upsilon+\epsilon \quad (6)$$

where B is the projection matrix, calculated using the kernel matrix such that

$$B= K*V*\lambda\text{^-}0.5 \quad (7)$$

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and $\upsilon$ is the regression coefficient computed using the ordinary least squares. Thus the non linear model between the dependent and independent variables is given by

$$y=\sum_{k=1}^{p}\upsilon(k)\lambda(k)\hat{} - 0.5\sum_{j=1}^{n}V\hat{}k(j)K(\bar{x}(j),x) \quad (8)$$

The regressors are tested, trained and fed to the proposed
non linear model. The comparative study of blaine prediction for manual and automatic data alignment has been compared as shown in Figure-5.

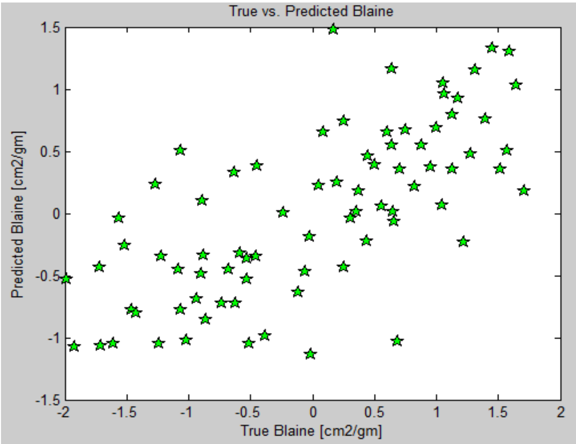


**Figure-5(a).** Blaine prediction for manual DR.

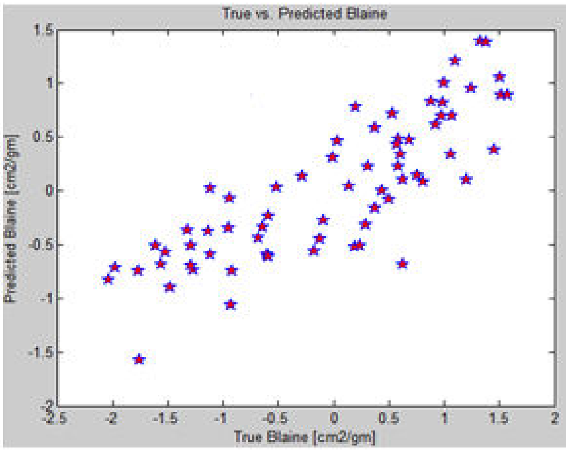


**Figure-5(b).** Blaine prediction for automating DR.

## 3. DATA RECONCILIATION

Data Reconciliation (DR) is a technology that uses all the informative input variable and mathematical model in order to find the error and automatically align the variables according to the dynamics of the industrial processes. The use of this technology will make the predictions more accurate and reliable, accurate predictions will help us to extract the information (such as delays) about the various variables. One of the advantage of automating the data reconciliation and alignment is it help to reduce the tedious task of calculating the dynamics for the regressors and it also aligns the data automatically. Data Validation and reconciliation is used for error identification and correction [10]. Data reconciliation approach had been implemented to propose a model that can calibrate population balance model to test results [11]. Data validation and reconciliation are also capable of handling thermodynamic model of a non linear system [12]. The block diagram of data reconciliation is shown in Figure-6.

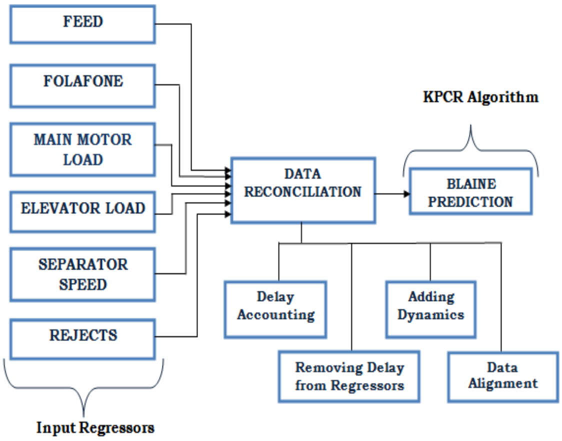


**Figure-6.** Block diagram for data reconciliation.

### 3.1 Steps for data reconciliation and alignment

a) The data collected through simulation was first checked visually. Regressors [Total of feed, folafone, main motor load, elevator load, separator speed and rejects and blaine] were arranged parallel.

b) Delay in the data was accounted. Delay details were confirmed through visual inspection as well as cross correlation results.

Total Feed-Blaine --------- 7 minute delay
Folafone-Blaine-------------8 minute delay
Main motor Load-Blaine---0 minute delay
Elevator Load –Blaine------0 minute delay
Separator speed-Blaine-----0 minute delay
Rejects-Blaine---------------0 minute delay

c) Except for folafone, 30 samples of total feed, main motor load, elevator, separator speed, rejects, blaine data were removed to account for 5 minute delay in folafone.

d) Once delay was accounted for blaine data was fetched every 15 minutes (90 samples). For every 15th minute blaine 10th minute data of total feed, folafone, elevator and main motor load was chosen as regressor. Going by this theory 30th minute blaine will have 25th minute regressor, 45th minute blaine will have 40th minute regressor and so on.

e) Since delayed data along with dynamics (one hour window) was required the initial one hour was used only to fetch dynamics data.

f) For regressors there was instantaneous total feed, total feed with dynamics, folafone with dynamics, elevator load with dynamics, main motor load with dynamics, separator speed with dynamics and rejects with dynamics.

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Figure-7 gives brief idea how the accuracy of the prediction varies for manual and automatic data reconciliation. Manual data alignment almost follows the peaks for the measured value of the blaine where as prediction using automatic data reconciliation is shrink and is more accurate.

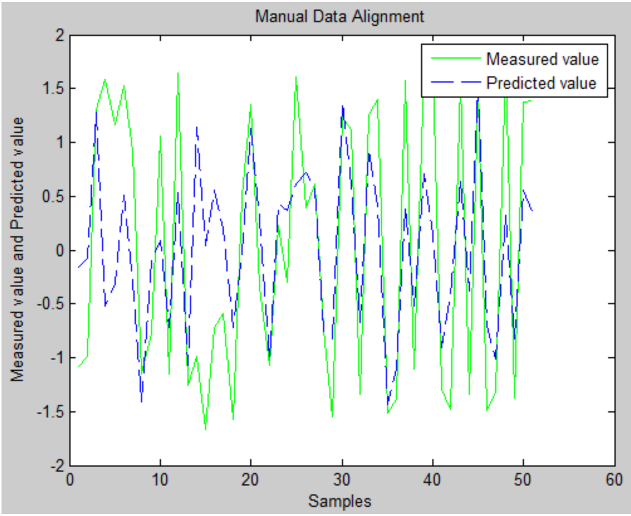


**Figure-7(a).** Prediction plot for manual data reconciliation.

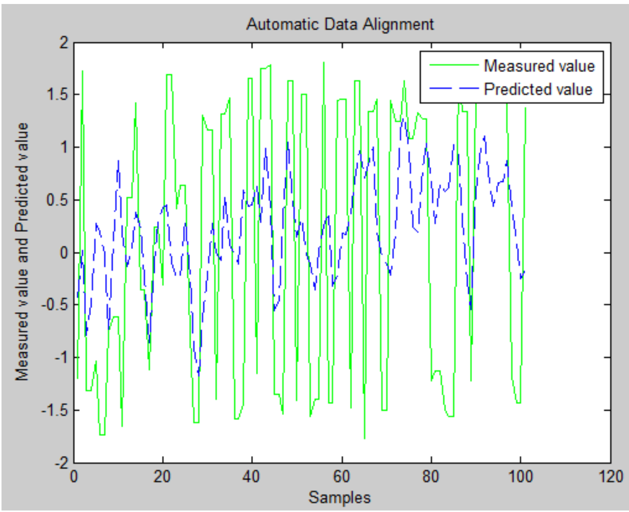


**Figure-7(b).** Prediction plot for automatic data reconciliation.

## 4. CONCLUSIONS

This paper gives a novel approach of aligning the data using data reconciliation technique. As in [7] ARX model is developed to effectively predict the blaine quality, blaine being the prime variable needs to be measured online continuously for better accuracy of predictions. Here it is proven that the results based on data reconciliation techniques are quite similar to the manual data alignment using KPCR. More over the automatic data alignment gives the more accurate predictions as it will help to avoid manual errors and can be used with the raw data directly taken from the plant. It also helps in updating the data whenever there are major changes in the process resulting in shift of operating region.

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