Flatness Prediction using Multivariate Data Analysis in Cold Rolling: A Review

Pooja Shindolkar  
PG Student,  
Department of Production Engineering  
VJTI Mumbai

Dr. B. E. Narkhede  
Lecturer  
Department of Production Engineering  
VJTI Mumbai

Abstract

This paper gives a review of the work done in the area of flatness prediction using multivariate methods. It describes the steps in the process of data analysis, used by the researchers. It also gives scope of research and available software for multivariate data analysis.

Keywords: Partial Least Squares (PLS), Principal Component Analysis (PCA), Mixture Probabilistic Methods

I. INTRODUCTION

Rolled sheet products are widely used in day to day life such as packaging products, printing, beverage cans, architectural components, etc. In case of flat rolling, one of the important output qualities of rolled products is a parameter called flatness. Rolling of both ferrous and non ferrous metals involves a great deal of complexity. Thus issues related to flatness arise in the rolling mill. The problems with flatness are observed in the cold rolling where the metal is rolled down to the thickness range of 6.3 to 0.2mm [9]. Off-flatness is mainly caused when there is a mismatch between the incoming profile of the metal being rolled and the roll gap shape. The incoming profile is a result of reduction at higher thicknesses (hot-rolling, strip casting) when metal can flow laterally. Profile thus generated cannot be altered during cold rolling. The roll gap shape on the other hand depends on many factors like incoming strip temperature, coolant level, bending of the work rolls and the intermediate rolls, the roll ground camber, roll deflection due to rolling loads, etc. Other than this the rolling speed, rolling force, lubrication viscosity, and entry and exit coiling tension also have an effect on the shape of strip.

The mathematical modelling of rolling process has evolved over time from the Orowan’s slab model [2, 4] used to calculate the rolling pressure, to asymptotic techniques and recent being Finite Element Methods (FEM) [1]. Mathematical modelling with FEM is time consuming and complex. Statistical modelling with multivariate methods is being developed for predicting flatness. Improvements in control systems and sensors now enable recording of numerous parameters during the rolling process at very high frequencies. The control systems can record data at frequencies as high as one reading per 2 ms. Thus a large amount of data is generated in the process. This data can be used to develop models using statistical techniques like principal component analysis, partial least squares regression, artificial neural network, fuzzy logic, mixture probabilistic regression methods, etc. The volume of data generated is large and these statistical methods are solved computationally.

The paper discusses the available methods of multivariate data analysis, and their application in cold rolling. Based on the review of papers a general flow chart is developed for the data analysis. Lastly it concludes with the scope for research in flatness prediction.

II. MULTIVARIATE METHODS

According to Mellinger [5] the multivariate methods are of two types’ factor analysis methods and classification methods. The factor analysis methods calculate new variables known as factors from initial variables, which are linear combination of initial variables. While classification methods deal with one variable at a time. The principal component analysis, partial least squares methods are actually factor analysis methods generally known as multiple canonical correlation analysis. The mixture probabilistic modelling method is an extension of the density based clustering method.

In a typical cold rolling process suppose there are m variables, n data points, then

\[ X_{m \times n} \]

is the matrix of input variables,

\[ Y_{p \times n} = \sum_{i=0}^{n} b_i X_i \]

is the output matrix.

Where \( p \) is the number of responses and \( b \) is the co-efficient

In simple linear regression change in \( i^{th} \) X variable will cause a change in Y linearly. But in case of rolling many of the input parameters are dependent on each other; this property is known as multicollinearity. This is quantified by the variance inflation factor as given by Mukhopadhay et.al [7]. In presence of multicollinearity, the principal component regression, partial least squares or the ridge regression method is used.
A. PCA & PLS

The PCA or PLS are mostly used in Chemometrics [12, 13]. These methods reduce the dimension of data. The PCA is used when we need to find the effect of the input variables. It is an unsupervised process. In that it doesn’t take the output matrix in consideration. While PLS on the other hand is a supervised method, it takes the target variable or predictor in consideration. Both PCA and PLS convert the initial data, into factors that are linear combination of initial variables [5]. For PCA these factors are known as principal components and for PLS it is known as the latent variables. PCA concentrates more on the covariance of \( X \) while PLS concentrates on covariance between \( X \) and \( Y \) [3]. It implies that the PCA gives information about hidden, simplified structures in a data, but that may not be associated with the shape of predicted surface. PCA also requires more principal components than PLS requires Latent Variables to fully describe the data. The PLS on the other hand is a robust form of redundancy analysis, seeking directions in the factor space that are associated with high variation in the responses but biasing them toward directions that are accurately predicted.

B. Mixture probabilistic method

The mixture probabilistic method is an alternative method for data analysis in case of multiple modes of operation as applied in [8, 13]. Multi-mode process in rolling implies the variation in width, thickness and grades of metal being rolled. The mixture probabilistic method can provide simple, accurate and easy-to-interpret local models that are integrated in some manner for the multiple operating condition issues. The probabilistic approach as opposite to deterministic approach of PCA and PLS claims to be more significant statistically for data analysis, inference, and decision making [13]. The probabilistic method is useful as it can deal with missing data, as it tends to find the relation between the input and output variables in the maximum likelihood framework. The basic principle of mixture probabilistic model is to approximate complex process with a finite collection of local models. Different variants of mixture probabilistic method have been used by researchers e.g. Gaussian mixture model (GMM), mixture probabilistic linear regression (MPLR), mixture probabilistic principal component analysis (MPPCA), mixture probabilistic principal component regression (MPPCR). The MPLR is used in [8] is found to be most effective. In this method the operating space is divided into \( k \) sub groups and a local regression model is established for each group. Each sub group has its own posterior probability and mixing proportion. Using the Baye’s theorem a weighted combination of all local regression models is obtained.

![Fig. 3.1: Flow Chart of Data Analysis](image-url)
III. DATA ANALYSIS

The process of data analysis remains similar irrespective of the tools (multivariate methods) used for analysis. The process of data analysis is generalized as shown in the flow chart in figure 3.1.

A. Problem definition

Problem definition is important part of any analysis. A proper problem definition can lead to much accurate results. The aim of multivariate data analysis is mainly online prediction of flatness, but in [10] the aim is to distinguish between factors resulting in a good and a bad coil, the differentiation made by the fact that the former has cracked surface. In [7] the aim is optimization of input parameters, the regression equation obtained is used as the objective function. While in [8] is mainly oriented for improvements in control system. The paper by Uppgard [11] aims at predicting post rolling flatness.

B. Data collection and cleaning of data

Depending upon the downstream product requirement there is variation in the gauge, width, material properties of rolled products. A typical rolling industry produces variety of products. While predicting flatness, it’s easier to assume one particular product type. Recently methods incorporating this variability are performed [8]. Data collection is done using the control systems in place. The integrated software can help to provide this data to the analyser. The data obtained at this stage is raw data; it has to be cleaned to be used for analysis. The cleaning of data can be a cumbersome task. Data can be lost, or random, irregular, until it reaches the analyser. It is recommended to use programming aid like R programming to obtain only the required data. For multivariate analysis only the steady state data is used. The acceleration and deceleration phase of the coil is discarded.

C. Selection of input and output variables

The selection of input variables is a crucial task. There are a large no of input process parameters. The control systems for rolling mills are fully automated in some places, while at others a certain amount of manual intervention is required. The data collection system allows the data to reach to the user for analysis. Based on the type of control system in place the inputs will differ. Usually rolling mills utilize flatness roll for measuring shape [7, 10, 11], but in case of [8], the DSR type of control system is used. It can help detect higher order and asymmetric defects. The pressure and temperature of the DSR pads is used as input for regression. For usual systems levelling, work roll and intermediate roll bending, intermediate roll shifting are the inputs. Additionally speed of rolling, tension of coiler and uncoiler, width, reduction in each pass, rolling load are also the inputs used. The variability of alloys can also be added as a categorical variable [7]. The selection of inputs is based on the available sensors and actuators, but also upon the experience of analyser. Other than this the units of the parameters also have an effect on the output. But this effect is neutralised by standardizing all the input data. The input parameters are given coefficients after solving the regression equation. The practical significance of these coefficients has to be verified by the analyser. If it’s not satisfactory, the inputs should be altered and regression must be performed again.

The data is divided into two groups training and test data. In [4] two third of the coils are used for training and remaining for testing. In [7] samples from one coil are taken, and two test sets are used for validation. In [5] two coils are analysed and result is verified with five other coils. In [11] the leave-one-out type of validation is used. A total of 25 coils are used and the model is based on 24 coils predicting the flatness for 25th coil.

D. Output Quantities and Graphs

The output in some papers is only represented graphically while in some there are certain measures used. For partial least square regression the R-square value is an important indicator of the success of regression. In [7] the R-sq obtained is 0.862; this value is satisfactory for analysis. Other than this it utilizes residual plots and residual histograms. A normal plot of residual implies a better regression fit. In case of [10], there is only graphical analysis. Loading plot, score plot, variance plot are used. In [8] the output is taken as Legendre coefficients and thus they are compared with each other. The contribution plot is used to define the effect of each factor on the output. In [11] Q value is used to compare the output of two methods i.e. partial least squares and artificial neural networks. This Q value is the mean of the difference between the actual and predicted value.

IV. CONCLUSION

The conclusion presented in [7] is divided in two parts. They have differently analysed the effect of parameters on the centre of strip and at the edges. For example variation in rolling speed has no effect on edge waviness, but an increase in rolling speed can increase centre buckle, but not that substantially. This is also in agreement with [8], where speed doesn’t contribute to the c2 (centre buckle and wavy edges) and c4 (quarter and edge centre waves) type of defect. However these papers differ in conclusion regarding bending control. [7] concludes bending has no effect while [8], infers bending contributes to c2 and c4. The reason for this ambiguity can be the difference in type of data used in analysis. In [7] the data used is for coil to coil while in [8] is within a coil. We can thus infer that bending can have an effect when we consider the instantaneous values during the rolling. In [10] the PCA results show that the main reason for breakage is roll forces and strip tension.
V. FUTURE WORK

The paper presents the work done in flatness prediction using different multivariate techniques. In order to carry out such type of analysis, a thorough knowledge of the multivariate methods is required. The literature available in this area is confusing. Also, the application of multivariate techniques was limited to chemometrics, its application in flatness prediction remains a major area of research. The proper understanding and implementations of multivariate methods can help identify the factors affecting flatness and lead to a better quality of rolled products. The models obtained from the multivariate methods can be converted to data products using programming software. These data products can thus be implemented in online control of flatness.

VI. SOFTWARE

The Statistica software developed by Statsoft dell is used by [7] for solving partial least squares. In [6] there is a tutorial for solving partial least squares in R programming. Others have used Simca P+ developed by Umetrix for partial least square. [10] uses the Unscramble software. Other than this, we can use Matlab, Minitab and R programming. If we want to generalize a method and repeat the same task again and again, we can program that in R and develop a data product. Other software’s are costly, but R is free software. We can choose one of the software or combine two according to our need.

REFERENCES