Vol.4. No. 1, July, 2015
141 - 152,ISSN : 0975-5446

Mild Steel Defect Diagnosis Using Tree Ensemble

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Abstract

The quality of mild steel coil manufactured is affected by many influential parameters during the manufacturing process. Among many possible defects, one of the defects is "coiling temperature deviation defect". This paper presents the most suitable technique for steel defect diagnosis using Business Intelligence. We have developed a layered approach that is a combination of data restructuring layer, statistical layer and machine learning layer. In Data restructuring data cleansing is done, in statistical layer normalization of data is performed and distance metrics is used for correlation detection. In final step fault diagnosis is done that uses a recent approach i.e. ensemble of trees (Random Forest), a machine learning approach. Though this approach is used in many fields, it has been observed that no work has yet been performed using this powerful technique in defect diagnosis in steel industry. This paper later discusses the produced results as rules that can be very useful for the industry to generate new controlling models for the process parameters.

Keywords : statistics, neural network, genetic algorithm, tree ensemble, decision trees.

1. Introduction

To be the best performing company in a sector, every company needs to be intelligent and quick in decisions making. The term 'Business intelligence' was hence coined for a technology-driven process for analyzing data and generate useful information to help business managers make precise decisions. BI encompasses a variety of tools, applications and methodologies that enable organizations to collect data from various internal and external sources, prepare and perform analysis to create reports, dashboards and data visualizations. BI programs include forms of advanced analytics, such as data mining, predictive analytics, text mining, statistical analysis and big data analytics. Various BI techniques are the basis of many research problem solutions.

Defect diagnosis is one of a major field of research in manufacturing industries. A defect in a product implies a loss to the company because this defective product may be sent for reprocessing, or may be sold at a lower rate or may be rejected. This leads to loss in terms of both money and time in huge amount. Many researchers find it interesting as the parameters that lead to cause the defect in manufacturing industries are usually non-linear in nature and many have complex dependencies, and hence this issue can be addressed in many ways.

In this paper we are address coiling temperature (CT) defect diagnosis issue for mild steel products of a steel manufacturing company. This deviation of coiling temperature; if it is low CT, forms a pan cake structure and those with high CT consists of polygonal grains with micro voids present at the grain boundaries in the final product.

We introduce various business intelligence techniques currently applied for fault diagnosis based on statistics and machine leaning such as PCA, linear regression and various machine learning algorithms like neural network, genetic algorithm, support vector machine, decision trees and random forest respectively. As a result of the study we find that random forest is the best performing algorithm amongst all other existing algorithms.

The paper briefly discusses preprocessing i.e filtration, missing value imputation and balancing datasets. Further we normalizes the data, calculates distance correlation (dCor) and variation in the dataset and finally the machine learning process accepts the data of previous steps and generates novel rules that cause the coiling temperature to deviate. The final stage uses Random forest, proposed by Breiman in 2001, which is recent extension of decision trees and integrates with the concepts of bagging of Boosting methodology and ensemble learning techniques.
It generates hundreds and thousands of trees using different subsets of data. It uses voting mechanism to generate the classification rules. The results in terms of most frequent rules generated the accuracy of the model in terms of OOB error and ROC curves are depicted.

This paper is organized as follows: SECTION 2 describes the manufacturing process of steel and sensor data generation, SECTION 3 discusses the problem statement SECTION 4 Discusses Related work, SECTION 5 describes the methodology, SECTION 6 discusses the results and SECTION 7 concludes the paper.

2. Steel Manufacturing Process and Sensor Data Generation

Steel manufacturing is a complex process that consists of various sub processes. During the process various sensors measure various related parameters. Basic compact strip plant has consists of a Tunnel Furnace maintains the slab temperature and reheats it. As the slab comes out of TF, it gets in contact with outer atmosphere that leads to creation of a layer which is removed by the descaler .Pyrometer 1 and Pyrometer 2 read the entry temperature of the strip. This reading gives the entry temperature. The number of measurements taken depends upon the length of the slab. The longer the slab larger the readings are. Average number of reading taken at entry side is about 240. Rolling Stands reduce thickness of the strip. Thickness is reduced maximum at S1 and gradually reduced in rest. S5, S6 and S7 majorly work on main aspects of providing Finished and final touch to Strip related to its shape and Profile. The number of reading agin in each of these stands also vary, in stand 1-3 the reading are taken every 1 or 2 ms, and from 5 to 7 stand the readings are taken every 4-8 ms. Thickness Gauge is for measuring the thickness of the strip. Multifunctional gauge measures Width, Profile, flatness, Thickness of the strip. And an integrated Pyrometer reads FT. It is used to get the readings of many Properties of coil and hence named so.

Laminar cooling is located between the Finishing Mill Stand F7 and Down Coiler. Its Main task is to cool down the strip in a uniform(laminar) fashion to Coiling Temperature(CT). There are 2 zones in laminar with a space left in between two zones. Each zone consists of 4 banks. Each bank consists of 4 sets of 2 sided nozzles. These nozzles pour water on the strip. There are two pyrometers that measure the Coiling temperature. Once the Strip leaves the laminar zone these pyros read the Temperature known as Coiling Temperature. Down Coiler, coils the strip. It has set of Pinch Rolls, Wrapper Rolls and Mandrel which wraps and coils the strip. Figure 1 shows the structure of a CSP mill from tunnel furnace to down coiler.

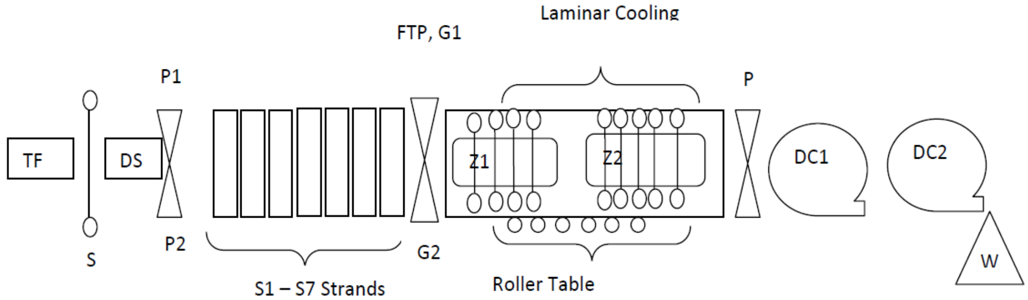

Figure 1 : CSP Mill

3. Problem Statement

Defect diagnosis has been an area of interest and research since few years. Defects in steel manufacturing are of two type's namely surface defects and dimensional defect. Surface defects are abnormalities seen on the surface of the sheet or coil such as hole, patches, cracks etc. The products manufactured that have characteristics which may vary from target characteristics found in finishing mill temperature, coiling temperature, thickness etc are called dimensional defects. These are all caused due to several reasons. When this deviation occurs, the product may be sold at a lower rate to the customer, may sell to some other customer who may accept the product or may be rejected. This leads huge monetary and times loss to the company.

We specifically concentrate on the dimensional defect called coiling temperature deviation. All these parameters are non-linear in nature. The exact reason for the deviation either high or low of target values are always a big issue to be solved that takes long time, sometimes in several days and sometimes not even found. The current approach followed in the steel manufacturing company is visualization technique. Using the graphs plotted for each process variable, a manual comparison of graphs is done for the pattern followed by the graph of the process parameters. If the process parameters follow the same pattern as coiling temperature graph, the resultant parameter is depicted as the causal parameter. This parameter is then controlled for the further processing of coils. This evaluation usually takes hours, or some time days together and many times the problem is left unsolved.

If an intelligent system generates all the possible rules for the causation of this problem, then the future problems may be avoided and save time, money and hard work. This work is to solve problem by generating rules that cause the coiling temperature to go high or low.

4. Related Work

Following is the discussion of various approaches implemented, related to the problem addressed.

4.1 Statistical Approach:

Statistics is a subject that has been very deeply explored in quality control and diagnosis in all industries. And will remain the foundation. Statistical process control and quality control are majorly used for generating various charts like running chart, p- charts and histograms for defect count. Authors in [1] discuss that statistical process control and design of experiment approaches do not provide conclusive results. [2] Used logistic regression, which is one of the traditional techniques used to determine the most influential process factors on the target process variable. Although the fitted model was statistically significant (p-values for Pearson and Deviance was 1.0; p-value for G was 0.0), none of the parameter estimates are found to be significant. Experts in [3] state that as a key aspect of quality Control and diagnosing, this root cause identification involves searching for systematic faults that explain the observed variability behavior by incorporating process knowledge. They propose a statistical tool for diagnosing the quality of solder pastes, the proposed MLPCA based regression coefficients clustering algorithm.
Still, these manufacturing processes are usually so complex that statistics alone cannot be used for generating rules for taking decision. Hence, in recent years data mining began to be applied to quality diagnosis and quality improvement in complicated manufacturing process, such as semiconductor manufacturing and steel making [5].As data mining predicts future trends and behavior which makes businesses upbeat, knowledge-driven decisions [1].
Many recent researches in fault detection and prediction have used data mining in their work.

4.2 Decision Tree Machine Learning Approach:

Experts in [5] have used C5.0 algorithm and found nine process variables to be influential on the response, defect types, and it also extracts ten rules associated with these significant input variables. They also show that logistic regression although used for defect analysis, gave unsatisfactory results. Instead CART I results in 64 % accuracy and CART II resulted in 92% accuracy. In [6] the author has proposed a knowledge based continuous quality improvement in manufacturing quality. They state that DMAIC(Define-Measure-Analyse-Improve-Control) is a problem driven approach. They have proposed a different model from DMAIC that is goal-driven approach. [7] Established an algorithmic decision tree, for the prediction of cracks evolution during hot rolling. Fahmi Arif, et.al.[8] have used a combination of PCA and ID3 algorithm in multistage to realize more faultless manufacturing.

4.3 Neural Network Machine Learning Approach:

Jarno J. Haapamali, et.al. [9] Have used data mining methods in hot steel rolling for scale defect prediction. The mean accuracy of the system was probably lower than 90%. [10] Also shows the applicability of regression and neural network in defect detection at Tata steel.[11] Presents a study that was performed using two nonlinear, nonparametric approaches, namely neural network and CART, to model the relationship between the qualities of the coating and machine readings.[12] Observers good results when using multi-layered feed-forward artificial neural network (ANN) models to predict the silicon content of hot metal from a blast furnace. Authors in [13] propose a structured model based on neural network with radial basis function for defect component analysis along with PCS.

4.4 Support Vector Machine Learning Approach:

Authors in [14] have shown a comparison between various mining algorithms for fault detection. They conclude support vector machines SVM have the best processing time and also overall high accuracy.[15] Propose a (SVM) based model which integrates a dimension reduction scheme to analyze the failures of turbines in thermal power facilities. In [16] authors have proposed a new approach for fault detection and diagnosis based on One-Class Support Vector Machines (1-class SVM) has been proposed. The approach is based on a non-linear distance metric measured in a feature space.

4.5 Association Rule Learning:

Authors in [6] stated that during manufacturing the process variable undergo variation. For that purpose they have used SPC to identify the variations and then used association rule to diagnose the cause of the problem.
Authors of [17] have used Association rules, Decision Tree and neural networks for detection of steel defects on surface. They tried using these algorithms to reduce product defects with Pits & Blister defect.
[18] Also shows Root-cause Machine Identifier (RMI) method using the technique of association rule mining to solve the problem of defect detection efficiently and effectively.

4.6 Genetic Algorithm Machine Learning Approach:

For prediction of scale defect prediction [19], shows the Genetic algorithm (GA) based method. They have used SOM for identifying the most promising variables and then used these variables in GA for the prediction. Average error was 0,0957[1/m2]. [20] uses genetic algorithm to create a controller for the HMT. Given current conditions (specified by the current HMT, which is referred to as the "operating point," and current values of the input variables), the solution should determine what changes need to be made to each variable in order to achieve a desired HMT at a desired time (some hours into the future).

4.8 Ensemble Based Approach:

In recent years, a number of data mining approaches for modeling data containing non linear and other complex dependencies have appeared in literature[21]. [22] Shows the results of decision tree ,tree forest and tree boost approaches. Tree boost and Tree forest both create ensemble of trees. Previous research [23] has shown that an ensemble is often more accurate than any of the single classifiers. [24] Evaluated 23 datasets with neural networks, decision trees and ensemble approaches. And they concluded that bagging is always more accurate than any other classifier. [25] states that for a small number of variables, the ANN classification was competitive, but as the number of variables was increased, the boosting results proved more efficient and superior to the ANN technique. [26] Found that random forest feature extraction showed comparable fault diagnosis performance for The Tennessee Eastman process, better fault identification performance for the simple nonlinear system, and better fault detection performance for the calcium carbide process; as compared to principal component analysis. [27] have presented a taxonomy of Random Forest algorithm and performed analysis of various algorithms / techniques based on Random Forest algorithm. The effectiveness of random forests on fault diagnosis of power electronic circuit experimented by determining optimal configurations of random forest in [28]. [29] Applied two different types of randomness, inserted into the individual trees of a random forest. They evaluated results obtained by other classical Machine Learning algorithms, such as neural networks, Classification and Regression Trees (CART), Naive Bayes, and K-nearest neighbor (KNN). They used a dataset of Gas turbine for fault diagnosis.

Authors in [30] state that random forest has achieved good results when being applied to medicine, biology machine learning and other areas but however they apply this method to machinery fault diagnosis for ship intelligent fault diagnosis of chain box.
Existing MLAs like decision trees, neural networks and genetic algorithms have good performance; still random forest performs better than these MLAs. They can deal with “small n large p”-problems, high-order interactions and correlated predictor variables. They are particularly an extension of decision trees as an ensemble approach. These combined classifiers work surprisingly well, are very stable and almost perfect “out of the box” classifiers.
In recent years, random forest has become increasingly popular in various fields, e.g., genetics, neurosciences, bioinformatics etc. Some work in stock market and software engineering is also seen. But its applicability and use in Steel industry has not yet been done for fault diagnosis. Hence in this work, we address the problem with random forest in steel fault diagnosis.

5. Methodology

Layered approach developed is broadly divided as data structuring layer, statistical layer and machine learning layer. The dataset we used is the real time data gathered from sensors of process related measurements. These measurements of process may be called sample readings taken at a moment of time for a particular location of the steel sheet being processed. Basically, the slab that comes out of tunnel furnace is of 30-40 m in length. As this slab enters the finishing mill, in stands, the length is increased and the thickness is decreased, to achieve the target dimensions. The measurements taken at every location of mill; is hence different, that results in imbalanced set of readings. Moreover, the measurements taken for each location of slab; or the thinner product; sheet; is called segments. This results in multiple segments reading. All these data are totally non-linear in nature. The best possible way of addressing issue is to visualize graphs and compare, which is already being done manually. But this does not guarantee finding the non linear dependency in totality. It needs human intelligence and experience also to identify the daily raising new issues. Hence we develop a new intelligent layered approach for addressing this. We address all the issues of data structuring as well as non –linear dependency using dCor. Moreover, steel data is extremely imbalanced dataset that is only 20-25 % of the production is found to be defective.

We in this work have worked with 1116 coils. With measurements in finishing mill to be 805500 instances 56 attributes for each stand attributes and laminar reading of 134616 instances. The 56 attributes in finishing mill contains both thickness affecting and coiling temperature affecting attributes, hence we then selected the features with the help of domain expert. This then was reduced to 22 features per stand. Further in study we found that the last stand was in most important stand, as the final thickness, and other dimensions produced from 7th stand matters. Figure 2, shows the model of the system.

5.1 Data structuring layer:

We now discuss the steps performed in this phase.

Filtration: We first filter the defective coils data removing head and tail part as 15%. Defective coils are those that are having final coiling temperature as +- 10 of the target coiling temperature for the coil.

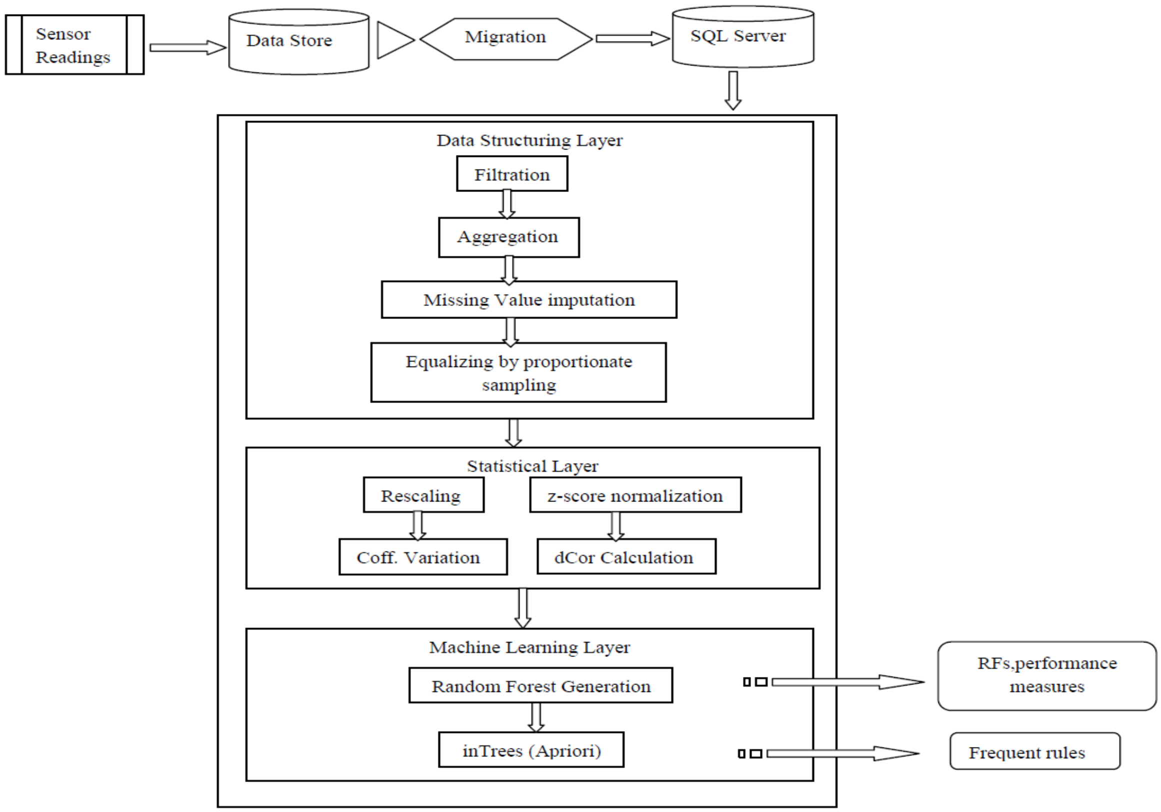

Figure 2: Model of the system

Aggregation: As the number of measurements of reach of the parameter in each phase is different, the segment number for entry phase, stand phase and finishing temperature reading phase have multiple entries. Hence we perform aggregation along with segment number to have one record per segment.

Missing Values imputation: aggregation leaves the data with missing values in stand 5-7 as the reading in these stands were taken every 4-8 ms. So, We fill these missing values with harmonic mean of last non zero value and next non zero value.

Equalizing by Proportionate sampling: The number of records in datasets are mismatched; ie. Not equal; hence we take proportionate samples of finishing temperature, keeping the entry and stand data to 100% records. We hence go for minimum loss of data. This still again leaves us with 300-500 records per coil depending upon the length of the coil.

We then later considered the columns that are related to Coiling temperature, leaving the thickness based columns aside, with the help of expert advice. As we do not have min-max values of all the parameters we take the mean for consideration of further calculation.

5.2 Statistical layer:

Rescaling: We rescaled these columns to 0-1 the selected features for using statistics calculation.
Calculate coefficient of variation: to find the variation percentage in the dataset column.
Normalizing: use z-score for normalizing.

Distance correlation: use of a recently developed non-linear distance correlation measurement by normalizing the column with calculating z-score. Using DCOR allows us to find whether the pattern of two the column measurement follow same pattern with non-literarily correlation.

Factoring target variable: We finally convert the coiling temperature as target with values H (high) and L (low) removing the dead and tail part. This indicates that the coils with coiling temperature reading with 10% defect reading more than the maximum target values to be regarded as H and 10% less than minimum target as L. All these steps have been shown in the fig 2. Table 1 shows the final column on which the further processing is applied. After this we worked with 280 instances.

Table 1: shows the final data for machine learning

Feature Name	**Type**	**Meaning**
CoilID	Same	Unique Id of Coil (9 character)
steel_gradeid	Same	Steel grade based on the chemical properties
Ischild	Derived	If the coil id contains
cvET	Calculated	Variation in Entry temperature
ref_hx 5 – 7	Same	Reference thickness of stand 5 to 7
Cvslbspd	Calculated	Variation in slab entry speed
dcorETSLBSPD	Derived	Distance correlation between entry temperature and entry speed
Dcorsspdft	Derived	Distance correlation between entry speed and finishing temperature
dcorETFT	Derived	Distance correlation between entry temperature and finshing temperature
dstdevwr_spd5 – 7	Calculated	Variation in work roll speed of stand 5 -7
dcorwrspd7_ft	Derived	Distance correlation of stand 7 work roll speed and finishing temperature
dstdevloo_act_tension5 - 7	Calculated	Variation of looper actual tension of stand 5- 7
dstddevagc_act_gauge_corr5 – 7	Calculated	Variation of actual gauge control stand 5 -7
dstdevslip_forward5- 7	Calculated	Variation of slip forward speed in stand 5 – 7
dCC_WR_CL_IN_TMP 5- 7FT	Calculated	Distance correlation between work roll cooling interstand temperature and finishing temperature 5 -7
dAvgCC_WR_CL_IN_TMP5 - 7FT	Calculated	Variation of work roll cooling interstand temperature and finishing temperature 5 -7
dCC_WR_CF_ES5- 7FT	Calculated	Distance correlation between work roll cooling fan entry side temperature and finishing temperature 5 -7
dCC_WR_CF_XS5- 7FT	Calculated	Distance correlation between work roll cooling fan exit side temperature and finishing temperature 5 -7
ftStdev	Calculated	Variation in finishing temperature
WATER_FLOW_TOP1-44	Calculated	Water flow top 1 -44
WATER_FLOW_BOT1-44	Calculated	Water flow bottom 1- 44
CROSS_SPRAY_ON_FLAG1-12	Calculated	Cross spray 1- 12
CTFlag	**Derived and factored**	**Coiling temperature flag (target)**

5.2 **Machine learning layer:**

We then apply a black box machine learning algorithm random forest to these values to generate trees. We generated 1000 trees using regularized random forest RRF library. As this technique is black box, we use inTrees framework to visualize the rules.

6. Results

We created 1000 tree ensemble. As this is black box, we used inTrees to see the non redundant rules in readable form. Table 2 shows 5 rules generated.

Table 2: Results

S. no	Length	Frequency	Error	Condition	Prediction	ImpRRF
1	3	0.431	0.14	dsspdft<=0.508998570380041&cvET>2.56580003133315& steel_gradeidin('SRCCRMB2','SRCCRMB6','SRCDRW01','SRCDRWG2','SRCLNC32','SRCTRN33')	L	1
2	3	0.07	0.07	dCC_WR_CF_XS5FT>0.342941113089022 & cvwr_spd7<=5.9229495821113 & steel_gradeid in ('SRCCRMB2','SRCCRMB6','SRCDRW01','SRCTRN33')	L	0.19
3	2	0.31	0.13	dCC_WR_CL_IN_TMP5FT<=0.250038712122941&steel_gradeidin ('SRCCRM06','SRCCRMB6','SRCDRW01','SRCTRN33')	L	0.13
4	2	0.02	0	dCC_WR_CL_IN_TMP5FT>0.250038712122941 & cvwr_spd7<=3.38814217368938	H	0.08
5	4	0.01	0	dCC_WR_CF_XS5FT>0.348773674867418& dCC_WR_CL_IN_TMP7FT<=0.0956215186912069 &dcorsspdft>0.464981634399104&steel_gradeidin('SRCCRB01','SRCCRM06','SRCCRM28','SRCCRP01','SRCDRWC1','SRCDRWG2','SRCLNC32')	L	0.06

Measured values "len" is the number of variable-value pairs in a condition, "freq" is the percentage of data satisfying a condition, "pred" is the outcome of a rule, i.e., "condition" => "pred", "err" is the error rate of a rule. And ImpRRF shows the most important rule, taking into consideration both error and frequency. Hence we see that even though rule 3 has high frequency, but due to error rate its importance decreases.

Rules show that when the steel grade in 'SRCCRMB2' ,'SRCCRMB6' ,'SRCDRW01', 'SRCDRWG2', 'SRCLNC32','SRCTRN33’ and a variation of entry temperature is above 2.56 and the distance correlation factor between entry speed and finishing mill temperature is less than 0.5, then the coiling temperature tends to go Low. Similarly when the distance correlation between work roll cooling exit side of stand 5 and the finishing mill temperature is greater than 0.3 and the work roll speed of stand 7 variation is less than 5.9 and the steel grade is

‘SRCCRMB2','SRCCRMB6','SRCDRW01','SRCTRN33’ then the coiling temperature tends to go L.

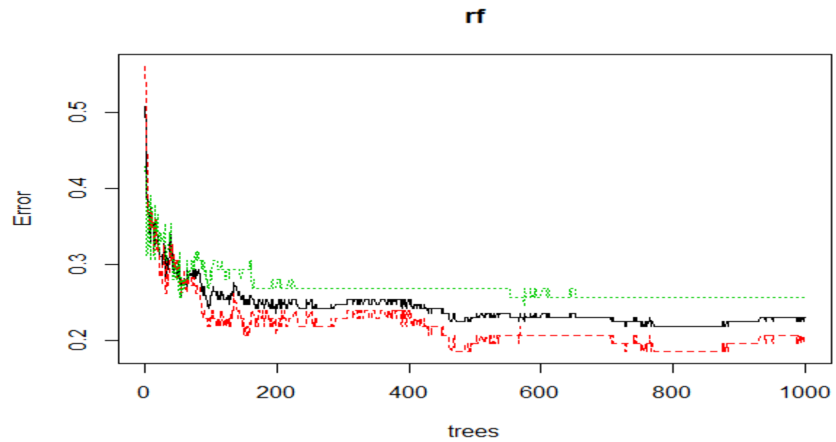

Figure 3 : OOB Error

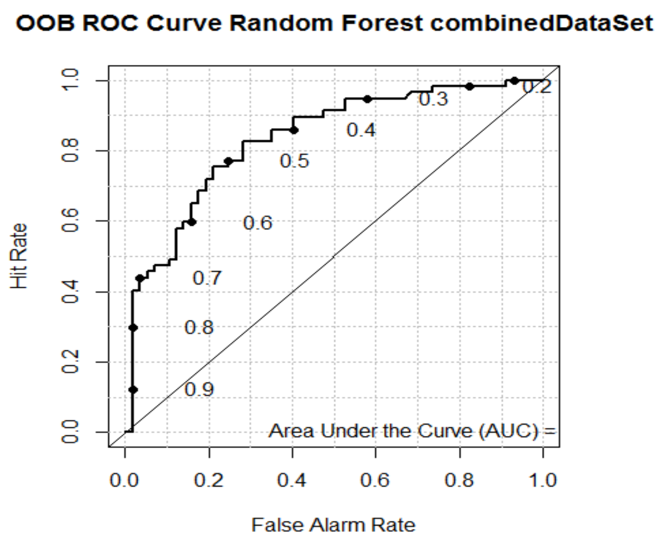

Figure 4: OOB ROC curve

Figure 3 shows the OOB error rate, that is the error rate calculated with the out of bag data,ie. 1/3rd set of data from left from boot strap sampling during creation of random forest. Figure 4 shows the OOB ROC curve, with an area under curve (AUC) calculated as 0.833 on test data. A score for a perfect classifier would be 1.

Hence we have generated useful results and rules for the defect less steel production mechanism. If these rules according to their stated importance are applied; for controlling the running production, will prove to reduce the defect causation.

7. Conclusion

The paper addressed the issue of defect cause diagnosis problem of steel industry. The dataset provided is highly non-linear, imbalanced with varied number of measurement. The data structuring layer addressed structuring issues, statistical layer performed normalization, rescaling, calculated variation and distance correlation. The last machine learning layer generated random tree ensembles. Further inTrees were used for visualizing the results of this so called black box technique. Although some work exists, using ensemble trees in fields like medicine, bioscience, stock market and software engineering, it has not yet been explored in steel dataset. We find novel unseen rules that may be reasons for the coiling temperature defect that will help the engineers to control the production according to the rules generated, or if they have seen any of the rules being applied to current ongoing process, the next production can be taken care.

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