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Integrated Approach for Human Understandable Steel Fault Diagnosis

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ABSTRACT
Businesses today need to look to have least faults in the products produced to remain forward in respective field. Customer provides requirements for the products by providing specific detailing that must be matched by the manufacturing company. Any product produced; that doesn't match with the said requirements, is then termed to have produced with a fault or defect. We in this paper are addressing a steel manufacturing company that creates large volume of data that is generated by a large number of sensors that are installed to determine various parameters that can be used to detect a fault in the coils produced. In mild steel coil, Deviation of the coil's final cooling temperature from the anticipated temperature creates defective coils. This paper presents an additional extended methodology for the detection of cooling temperature deviation defect diagnosis con sisting of four phases, namely association identification, statistical derivation, stochastic classification, and fuzzy inference, for enhanced user understanding.

Keywords:- Random forest, boosting, neural networks, classification, fuzzy logic

I. INTRODUCTION

It has always been a need to focus on quality product for any product or sector. The ultimate quality of manufactured goods being produced cannot be compromised, as the production is usually done on the basis of customer request. Data Science, that revolves around statistic, algorithms, models, union of multiple models, mathematics, and many others. Talking in terms of current technology as Data Science, where data mining becomes a integral part, many data mining based solutions have been explored by various industries and academicians since last few years for addressing fault diagnosis. The Data Science can be used for producing analytical reports, dashboards and visualizations. It primarily includes data mining, text mining, statistical analysis and big data analytics.

Steel Manufacturing industry fundamentally concentrates on production of defect free customer specific goods. Defect Diagnosis has been of keen interest in any manufacturing industry. Here we are looking at steel manufacturing industry that truly is very complex with many sub processes involved. So, the diagnosis of defect has procured a special interest in Steel firms.

Occurrence of difference in the characteristics with the features of final products is called as defect. Defects are of two types, surface defect and dimensional defect. Surface defects are the planes or boundaries that separate a material into sections or an area encompassing the same crystal makeup but different orientations or a patch or a hole. Dimensional defects are variation in dimensional properties from the anticipated assessment like width, thickness, profile, coiling temperature. Defects related to finishing temperature and some of the others require magnetic particle inspection (MPI) which cost very high and are carried out if the customer demands to get it done. We in this paper are concentrating on coiling temperature deviation defect that is a dimensional defect, and are providing extension to the earlier paper [29].

Statistics has been a essential approach of inspection in many businesses, and has been being used for fault diagnosis too [29]. Quality assessment has been performed by the authors in [2]. They have used linear regression and MLPCA grounded regression coefficient to perform the same. Processes of Steel engineering are typically too multifaceted, so statistics alone is not sufficient. Therefore, data mining is used for quality analysis and improvement in complicated manufacturing process like semiconductor and steel making in recent years [1,3,29].

Most current research into detection and prediction of faults has used data mining techniques in their work. Some used algorithms were neural networks, genetic algorithms, support vector machines etc.

As we extend to the work done in the earlier paper [29] that has been built on stochastic ensembles trees named as random forest; a machine learning approach for steel defect diagnosis was the first work in this field, as per out study. Breiman has proposed Random forest as a division of decision trees and incorporates with the concepts of bagging of boosting and ensemble learning techniques [29][30]. It makes use of voting means to generate the classification rules. It has become focused research area in various fields like stock market studies, neuroscience, biotechnology and software engineering has so far proved to outperform other machine learning algorithms such as NN, decision trees, SVM etc.

Hence in this paper, the human explicable defect diagnosis problem has been presented with fuzzy logic. So the sequence of tasks to be performed goes as finding Association rules, creation of Random forest and finally application of Fuzzy Logic. The last step makes the whole model stronger and eventually understandable by humans with or without the field experience. Associative Classification comprises of four phases namely data preprocessing, association identification, statistical derivation and classification. At the end, fuzzy logic is used to make it understandable by humans of the domain and non domain. Different issues of data structuring like missing value imputation, filtration and balancing datasets have been addressed in [30].

The identification of strongly associated attributes, normalization of data, calculation of distance correlation (dCor) and variation in the dataset that has been shown in [29]. The classification phase obtain data from previous steps to execute feature selection with variable importance using random forest and produce 1000 trees. Then, fuzzy rules are applied to generate a rule on which the decisions can be taken by engineering domain person or others that cause the coiling temperature to deviate.

This paper discusses the results in requisites that any user of steel industry domain or others can understand. Rules are being displayed using linguist terminology. Fig 1 depicts the steel manufacturing process. It shows the structure of a CSP mill from tunnel furnace to down coiler.

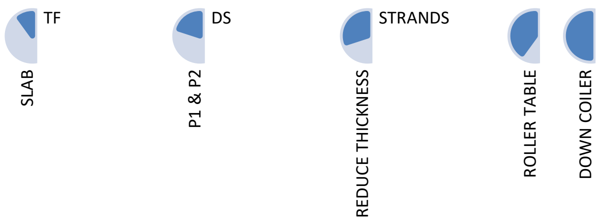

Fig. 1 CSP MILL

The paper is organized as follows. Section II elaborates related work, Section III discusses Fuzzy Logic and its working mechanism, Section IV includes the methodology, Section V discusses results and Section VI concludes the paper.

II. RELATED WORK

We discuss various approaches used to address problem of fault or defect diagnosis.

Decision Tree approach was used by authors [29],[30],[4],[5] [6] for quality and defect analysis. The experimentation by Berna Bakir et al. [4][31] used c5.9 for defect analysis, with a global pruning with 75% severity to evade over fitting. It is observed that nine process variables were having important effect on response defect types. The logistic regression when used for defect analysis, gave inadequate results. The CART I and II have given 64% and 92% accuracy respectively as result.

The experiments proposed knowledge based continuous quality improvement carried out by Shu-guang He et al.[5][31] [29],[30] for increasing manufacturing excellence. The goal –driven approach is used to propose an unusual model from DMAIC(Define-Measure-Analyze-Improve-Control). There were 4 factors in each record from random collection of 1000 records. The records were classified based on defect rates and identified as H if defect rate > 3.0% else others as L. Decision tree C5.0 is used for the analysis.

Martin Vlado et al. in [6], [29][30] recognized an algorithmic decision tree, to forecast of cracks development in hot rolling. The prediction of V-shaped and U-shaped cracks in steel slab using C4.5 program during hot rolling is assessed in the paper.

The applicability of Neural Networks for the stated purpose has been addressed in [8], [9], [10], [11], [29][30] and [7].

The diverse average measurements of process with different frequencies are collected by Jarno J. Haapamali, et al. in [8] [31] [29][30] . The measurements were gathered for 1326 steel strips with 50 variables and 127 averages values. The self organizing map was used to handle this which can visualize non-linear dependencies. The work obtained mean accuracy lower than 90% for scale defect prediction.

Shankar Kumar Choudhari et al.[9] [31] [29][30] also exhibit the usability of regression and neural network in defect detection at Tata steel.

M. Li. S. Sethi et al. [10] [31] [29][30] offered came up with hundreds of variables related to various engineering processes involved in manufacturing coated glass that resulted in footing results by using data mining techniques. This work used neural network and CART to model the relationship between the qualities of the coating and machine readings.

The multi-layered feed-forward artificial neural network (ANN) models were used to forecast the silicon content of hot metal from a blast furnace by Bulsari et al. [11] [31] [29][30]. The time lags between each of the range of inputs were performed and the silicon content (output) was recognized to be important.

FahmiArif et al.[7] [31] [29][30] carried out defect component analysis by implementing a structured model based on neural network with radial basis function along with PCA for both linear and non linear data. It is difficult to interpret, is "black box", needs greater computational weight and is prone to over fitting form the disadvantages of the approach. However accuracy of 90% was obtained.

The SVM based approaches have been used to address the issue by authors in [12,13,14,29,30]. GolrizAmooee et al. [12][31] demonstrated contrast between mining algorithms for fault detection. They showed that the use of Support Vector Machine (SVM) has given most excellent processing time and accuracy. The C5 model is used to produce predictions rules.

The integrated SVM based dimension reduction scheme was used to examine failures of turbines in thermal power plant by Kai-Ying Chen et al. [13] [31] [29][30]. They have shown that the SVM performs the best than linear discriminant analysis (LDA) and back-propagation neural networks (BPN) in classification.

A model with One-Class Support Vector Machines was proposed by SankarMahadevan et al.[14] [31], considering non-linear distance metric measure in a feature space used for fault detection and diagnosis. But, the methods are high algorithmic complexity and exhaustive memory usage.

Authors in [5,15,16] [29][30] proposed use of Association rule in defect diagnosis. As process variables in manufacturing industry go through variation.

To identify the cause of the problem causing a defect based on variations, Shun Gang He et al. [5] [31] [29][30] proposed a combination of association rules and SPC (statistical process control). The model was executed with support and confidence of 65% and 80%. They reached to conclusion that 95% of the products that were failed in the test were due to line 4, test with 62,592 products, out of which 16,905 products failed the test.

Sayed Mehran Sharafi et al. [15] [31] [29][30] worked with 186 variables later condensed to 36 after performing preprocessing. Association rules, Decision Tree and neural networks were applied for surface defects identification, particularly pits & blister defect. Depending on the carbon content and other elements, the accuracy of each individual the model varied. Wei Chau Chen et al. [16] [31] [29][30] addressed defect detection depicting Root-cause Machine Identifier (RMI) by, defect case based analysis.

To forecast scale defect prediction, Jarno Haapamaki et al. [17] [31] [29][30] depicted the use of Genetic algorithm (GA) and neural network. The variable selection and the prediction was done by GA with average error of 0,0957[1/m2] by self organizing map.

A genetic algorithm based HMT controller was developed by Danny Lai [18] [31] [29][30] works with given current HMT (operating point) and returns the amendments to be made to each variable at a given time.

Many approaches have been followed for modeling data containing nonlinear and other complex dependencies. Results of decision tree, tree boost and tree forest approaches have been shown by Tarun chopra et al. [19][31] [29][30].

Research performed in [20][31] [29][30] has shown that often ensemble is more precise than single classifier.Opitz D, Maclin et al. [21][31] [29][30] used 23 datasets and evaluated work with neural networks, decision trees and ensemble approaches. They proved that bagging is more precise than any other classifier.

The ANN classification presents good for smaller number of variables, but as the number of variables is increased, the boosting process to be more efficient and better to the ANN stated by Byron P. Roea et al. [22][31] [29][30].

Lidia Auret et al. [23][31] [29][30] observed 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 PCA.

Vrushali Y Kulkarni et al. [24][31] [29][30] carried out analysis of different techniques/ algorithms based on random forest algorithm and offered taxonomy for Random Forest too.

Effectiveness of random forests on fault diagnosis of power electronic circuit experimented by Jin-Ding Cai et al. [25][31] [29][30].

Manolis Maragoudakis et al. [26][31] [29][30] applied two different types of randomness, placed in into the individual trees of a random forest. The work evaluated results of other classical machine learning algorithms, such as neural networks, Classification and Regression Trees (CART), Naive Bayes, and K-nearest neighbour (KNN) carried out on Gas turbine dataset of for fault diagnosis.

Random forest worked well when it is applied to medicine, biology machine learning and other areas. The authors in [27][31] [29][30] applied this method for ship intelligent fault diagnosis of chain box. Random forest performs better than other existing MLAs such as decision trees, neural networks and genetic algorithms.

Veena Jokhakar et al. in [29] state that Random forest has outperformed other ML algorithms for the stated hybrid problem. Experts in [32] have presented defect detection system was for reflective and transparent surfaces. They have proposed a technique that is using fuzzy logic based on image segmentation. They had used 23 pieces of glass for testing. They achieved highest sensitivity value of 83.5% with proposed algorithm.

We in this problem still have addressed the issue of defect analysis by considering deviation percentage of process parameters and similarities of data movement along with human understand ability.

Therefore, this paper proposes a unique model that addresses the above mentioned problems and achieves higher performance.

III. FUZZY SYSTEM

The term "Fuzzy" means vague. Fuzzy Logic is a control system of an classification phase n-valued logic system that makes use of n the degrees of state "degrees of truth "of the inputs and produce outputs that depend on the states of the inputs and rate of change of these states (rather than the usual "true or false" (1 or 0), Low or High Boolean logic (Binary) on which the modern computer is based. It fundamentally provides basis for loose reasoning using inexact and imprecise decisions and allows using linguistic variables. It is defined by Fuzzy linguistic variables and fuzzy expression for input and output parameters. Hence this can be used in real life to get valuable reasoning. It has been applied to many fields ike control systems to many AI application. Figure [2] shows the architecture of fuzzy logic.

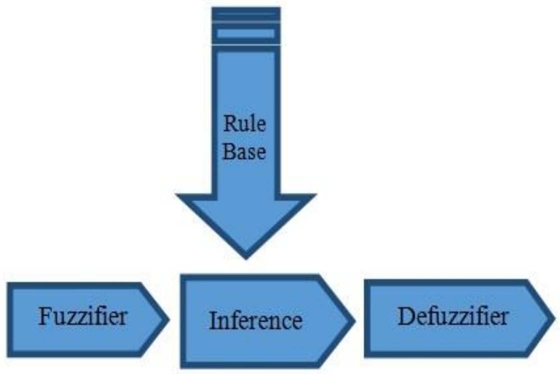

Fig. 2 Architecture of Fuzzy Logic

Based on the literature study, random forest was chosen to address the current problem. As random forest is a rule based classifier, but the output that was achieved was not understandable by a person without domain information. To be specific, it was only understood by the person working in the automation cell. As we have covered authors in [32] have used fuzzy logic for defect diagnosis.

Our work introduces Fuzzy Logic in Steel engineering for fault analysis that is the extension of the work previously done for better user usability and understanding.

IV. METHODOLOGY

We propose a new extended model to resolve the problem by considering fuzzy logic as the final step to make it understandable by all. We had earlier worked on association rules identify to associations, distance correlation to find the non linear as well as linear dependency, classification was performed using random forest the data and here in this paper we introduce finally Fuzzy Logic to give a clarity to non-domain users.

The work has been done with 1116 coils. With reading of finishing mill to be 805500 instances 56 attributes for each stand attributes and laminar reading of 134616 instances. The 56 attributes in finishing mill comprises of both thickness affecting and coiling temperature affecting attributes, hence we then selected the features with the help of domain expert. Fig 3 shows the model of the system.

Fig. 3 System Model

A. *Data structuring layer*

Data structuring has been explained in detail by Veena Jokhakar et al. in [30] that included the steps viz; filtration, aggregation, missing value imputation and equalizing.

Based on the data, data reduction increases the accuracy of the model. We had performed data reduction with finding strongly related attributes by using apriori algorithm. Veena and Patel S.V discuss this in their earlier paper [29][30] about the results they achieved .

B. *Statistical layer*

This layer had the statistical computation like rescaling, variation, and normalization, distance correlation, to find the pairs of column with linear and non linear correlation.

C. *Classification layer*

This layer generated 1000 trees using ensemble technique. Being black box, inTrees was used to visualize. This has been described by Veena Jokhakar and Patel S.V. in [29][30].

TABLE I

ASSOCIATION RESULTS

Rules	Support	Confidence	Lift
CC_WR_CF_XS7=j => CC_WR_CF_ES7=j	0.0943	0.9439	9.439
CC_WR_CL_IN_TMP5=g => CC_WR_CL_IN_TMP6=g	0.0942	0.9422	9.422
CC_WR_CL_IN_TMP6=g => CC_WR_CL_IN_TMP5=g	0.0942	0.9422	9.422
CC_WR_CF_ES6=c => CC_WR_CF_XS6=c	0.0941	0.9416	9.416
SLIP_FORWARD5=j => CC_WR_CF_XS6=j	0.0909	0.9098	9.098
WR_LIN_SPD5=g => CC_WR_CF_XS6=g	0.0881	0.8811	8.811
MEA_TEM_FRONT_FM_AVG=h => SLAB_TRANSFER_SPD=h	0.0757	0.7579	7.579

There are a number of machine learning classification algorithms that can be applied to this problem such as SVM, decision trees, tree boost, neural networks etc. We have evaluated our problem with Tree Boost, neural network, Decision tree and SVM. All these algorithms are doing well for respective with their own strengths. We have found that Random Forest gave the best result.

These work further proceeds with the application of Fuzzy Logic.

The steps of rule mining are briefly given below:

1. Select the fuzzy inputs X and outputs Y.
2. State their universal set and fuzzy set.
3. State the linguistic variables and their membership functions.
4. For an input ix one can use the membership function of input X to find out which linguistic variable Ipt it belongs to.

The corresponding output Oy is linked with the linguistic variable Opj by the membership function of output Y.

5. Taking the linguistic variable of the fuzzy input and the corresponding linguistic variable of the fuzzy output. Fuzzy rule can be extracted as

IF Ix is Ipi THEN Oy is Opj

So we have

dstdevwr_spd7<=10.20 & dstdevwr_spd7>6.15 & dwrlinspd56>0.93 THEN CT is High

The fuzzy inputs are (1) MEA_TEM_FRONT_FM_AVG, (2) SLAB_TRANSFER_SPD, (3) CC_WR_CF_ES6, (4)

CC_WR_CF_XS6 and other 19 variables while the fuzzy output is the Coiling Temperature.

TABLE II: CLASSIFICATION RULES

No	Len.	Frq.	Er.	Condition	Prd	Imp.
1	3	0.52	0.18	steel_gradeid in c('SRCCRM06','SRCCRM28','SRCCRMB2','SRCCRP01','SRCDRWC1','SRCDRWG2','SRCLNC32') & dcorsspdft>0.185236220573201 & dstdevwr_spd6<=5.3779382339644	H	1
2	4	0.34	0.07	steel_gradeid in c('SRCCRM06','SRCCRM28','SRCCRP01','SRCDRWC1','SRCDRWG2','SRCLNC32','SRCTRN33') & dcorsspdft>0.18 & dstdevwr_spd6<=4.09 & dstdevwr_spd6>1.00	H	0.37
3	5	0.08	0.15	steel_gradeid in c('SRCCRM06','SRCCRMB2') & dCC_WR_CF_XS7FT>0.11 & dslipccwrxs<=0.001 & dwrlinspd56<=0.95 & dwrlinspd56>0.82	L	0.21
4	4	0.06	0.18	steel_gradeid in c('SRCCRM06','SRCCRMB2') & dslipccwrxs<=0.0007 & dwrlinspd56<=0.94 & dwrlinspd56>0.82	L	0.19
5	3	0.16	0.07	dstdevwr_spd7<=10.20 & dstdevwr_spd7>6.15 & dwrlinspd56>0.93	H	0.17

V. RESULTS

We had created 1000 tree ensemble and 7 variables were applied at each split. As this methodology is black box, redundant rules were generated and we had used inTrees to remove the redundant rule. Table II partially shows 5 rules generated. Measured values len,frq,prd,er correspond to variable-value pair,% of condition getting satisfied,result and error.

It can be seen that the entry temperature and speed are the major cause of issue. we now consider these ouput to act as input to out Fuzzy model , we use the command "rule" to form the "rule base". This forms it as "a1" "and" "b1" "and" "c1" "and" "d1" "->" "e1".

The model is built by using the function frbs.gen().
This gives the putput as "IF" "input1" "is" "a1" "and" "input2" "is" "b1" "and" "input3" "is" "c1" "and" "input4" "is" "d1" "THEN" "output1" "is" "e1".

There the table [3] shows the linguistic variables set for the model to be developed.

TABLE III: LINGUISTIC VARIABLES

Linguistic variables	Assigned values
Less deviation	dstdevwr_spd7<= 11
High	XS7FT>0.11

Hence, we get results as
Stdwr_spd7 is having less deviation & XS7FT is high then Coiling Temperature is high

The rule is read as if the similarity between slab speed and finishing mill temperature is less and the exit finishing mill temperature is is high then the coiling temperature is high
Now, this is a clearly understandable rule , that can be understood by any person.

It can be observed from the above table that, random forest outperforms all the rest of the algorithms applied on the same set with highest value of accuracy of 95% and other performance measurement statistics. Moreover we also see that combining fuzzy logic to the model make it more efficient to be used by the user. This proposed model is a combination of data mining and statistics considering association identification, classification, statistics and fuzzy logic , gives a better understanding of defect analysis specifically with distance correlation a statistically interpreted data information, achieves higher accuracy than other applied work for defect cause analysis.

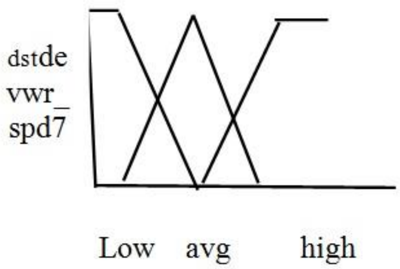

Fig. 4 Membership Functions

VI. CONCLUSION

Aspect of this paper is to introduce the fuzzy logic as an extension to the already been and addressed work on defect diagnosis on steel manufacturing on the cooling temperature. This is a model that works as machine learning algorithm, with a combination of association rules, Random forest and fuzzy logic and for defect cause diagnosis problem of steel industry. The dataset gathered is a genuine dataset that was extremely non-linear, imbalanced with diverse number of measurement. We hence have prepared the facts first to be able to apply for machine learning. Strongly connected attributes are first identified using association rule mining to generate, mysterious reasons of the variation caused in coiling temperature. After working with many algorithms like NN,SVM,BOOSTING etc., it is found that random forest outperform all the rest of the applied algorithm. We found new unobserved rules that may be cause for the coiling temperature defect that will help the engineers to control the production according to the rules generated and it further helps in next production. We have used fuzzy logic that makes the rules readable by explaining the rules using the linguistic variables. The proposed model outperforms other fault / defect diagnosis mechanisms by obtaining accuracy of 95% and in more readable form.

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