

# Prediction of Coil Breaks in SPM using Artificial Neural Network

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**Abstract** -Coil breaks are persistent menace for almost every Cold Rolling steel plant. The uncertain demand flow pattern combined with extreme competitive environment has made the steel industry Quality driven. The steel industry consists of processes like Iron Making, Steel Making, Casting, Hot Rolling, Cold rolling, etc. Cold rolling being end process considers defects as wastage of all previous processes, costs, and time invested to achieve the product. Quality defects are considered grave problems for any cold rolling production line. The study aims to predict the formation of coil breaks by use of an artificial neural network at Skin pass mill. The study is conducted at the Tata Steel Cold Rolling Complex (CRC-West) at Tarapur Midc, Boisar. At CRC-W the production lines present are Pickling, 4 hi Rolling mill, Cleaning, Annealing, Skin pass mill, Slitting, Multi blanking line, Cut to length. We are concerning ourselves with the formation of coil breaks at the Skin pass mill. The coil breaks occurs as a result of non-uniform yielding behaviour post forming. Typically observed in Deep drawn and extra deep drawn material, however it can also occur in under stabilised IF steel.

Prediction of the formation of coil breaks can be done by an artificial neural network program. An ANN is computing system that learns to perform tasks by considering examples and data sets, generally without being programmed with task-specific rules. The appropriate ANN model is to be developed. The input and output parameters of each of these cases have been decided based on criteria as discussed later. With the Input and Output parameters decided, now the dataset can be taken from the tracking software at the Skin pass mill. The Artificial neural network must be trained so as to increase reliability. The trained ANN must now be validated and tested using a program called Python. The ANN will start predicting if coil breaks will occur or not after skin passing using parameters. The accuracy of ANN will increase as size of

dataset increases so for further applications, the ANN could be upgraded to include real time monitoring and prediction.

**Key Words:**Coil Breaks, Skin Pass Mill, Artificial Neural Network, Cold Rolled Coils, Non Uniform Yielding, Data Sets, Load, Tension, Prediction, Analysis

## 1. INTRODUCTION

The Coil breaks mainly occur due to the material internal defects. The occurrences of coil breaks and their causes have not been studied properly. This dataset is originally from Tata Steel depository. The objective is to predict whether a coil break occurs or not. We use Python to make the artificial neural network. Python is an important language for machine learning as it removes complex operations. Its extensive library and machine learning concepts are very helpful. We use supervised learning, in which datasets and learning is predefined to make the model. The work for project is undergone at Tata Steel, Tarapur which is a cold rolling plant.

## 2. DATA SET

The dataset contains the 9 attributes in total. The inputs as a whole are of cold rolling coils. The dataset is in two forms namely Data depository and Defect data. The Data depository is very useful to solve the major problems faced at the company due to its availability and storage of data. The Defect data is made available by the Quality department which collects the relevant data regarding all the defects in the company. The month of September is taken as a random month. We first took the coil breaks occurring in the particular month of September. The overall input data contains Average speed of the mill, Rolling force actual average, Elongation Average, Elongation SP average, POR tension average, Recoil tension average, Negative bending, Positive bending, Output in form if coil break occurs or not. Now we will trace which coils have shown coil breaks in the Quality checks. The coils

which have coil break will be tagged as “1” for output and the coils which do not have coil breaks will be tagged as “0”. The skin pass mill has many defects, but the coil breaks are shown to be most persistent one and have nearly 50 % of defect tonnage of all defects at the machine. The skin pass mill is nearly end process for cold rolling process. So any defects at this step would result in the loss of all factors applied for the material.

### 3. METHODOLOGY

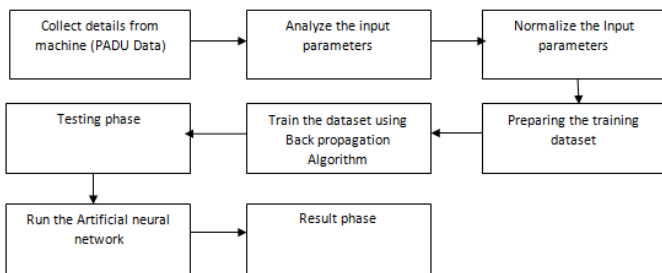


Fig 1: Block diagram for methodology

The methodology involves the collection of data which can be done by data depository. We have already specified the procedure. The analyzing of the input parameters involves data preprocessing by scaling values in form close to 0 or 1. The scaling of data is important as it helps in the further calculations. The normalizing of the parameters involves making data correlations; it helps for establishing relationships between the data values.

The Data is then portioned in ratio of 80:20. The further process involves the training phase in neural network which would take 80 % of the data set and train it.

The Logistic regression is a predictive analysis module which is used when the output or value takes a form of binary type of data. Here the output is 0 or 1 which is binary. The K neighbor classifier is a statistical recognition module. It is used to determine the nearest value to the given answer. So the issue of the which is nearest 0.6 or 0.4 to 1 can be easily solved. The Gaussian naive Bayes is used as a conditional probability, It assumes all the factors have impact on results and calculates probability accordingly. The Support vector classifier is approximate line which divides two data like coil breaks occur or not on a graph. The Testing step is also an important one as the 20 % of the data testing will enable further increase in accuracy in the model.

The artificial neural is now run, we create a fake coil which would be required to input data for which it is to be tested. The input for the coil which is to be checked will involve all the inputs only the coil break input in form of 0 or 1 is not to be input. The artificial neural network will predict this data in array form with 0 or 1 as output.

### 4. EXPERIMENTS

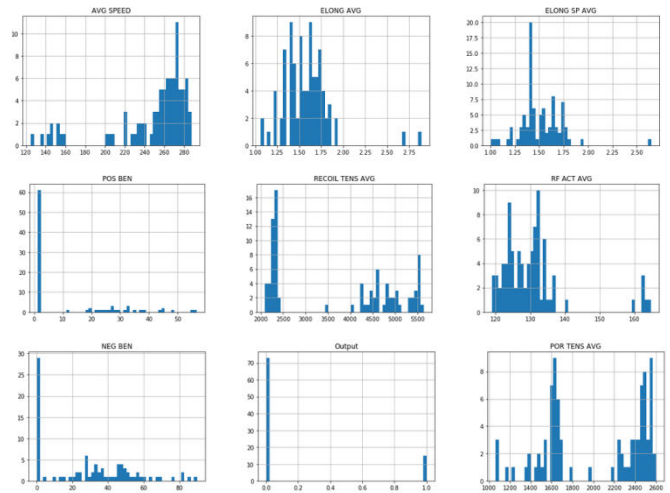


Fig2 : Histogram for all the inputs

The histogram shows the input relationship for individual inputs. The density is high at the Average speed, Elongation average and rolling force average. But the clarity is not seen for the inputs. We have now seen the possible relations in these three inputs on output. Further perfection can be achieved by the program output.

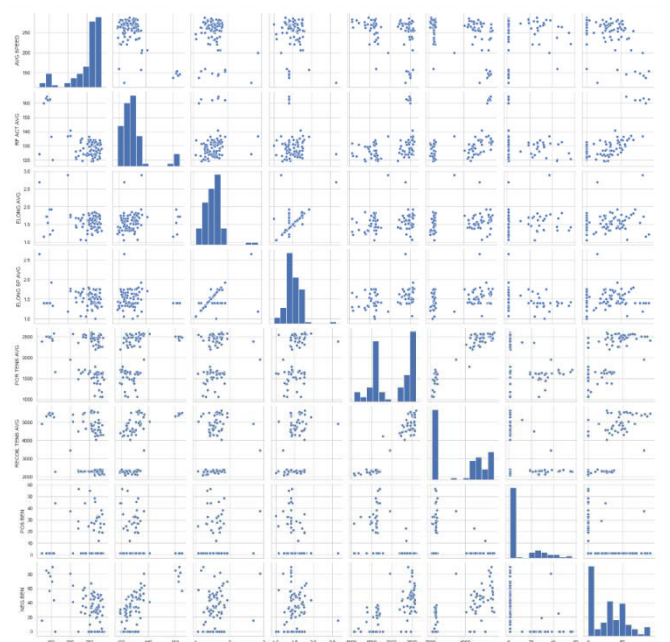


Fig 3: Pairplot

Starting with pair plot we will start exploratory analysis. One thing that we were able to deduce from this image was that all the parameters overlap for the Outcome value, i.e., no matter if coil break occurs or not, you can have the same parameters.

Next in our list was the heat map plot which did give us some insight about the parameters and the relation it has with the other parameters and the Outcome as well.

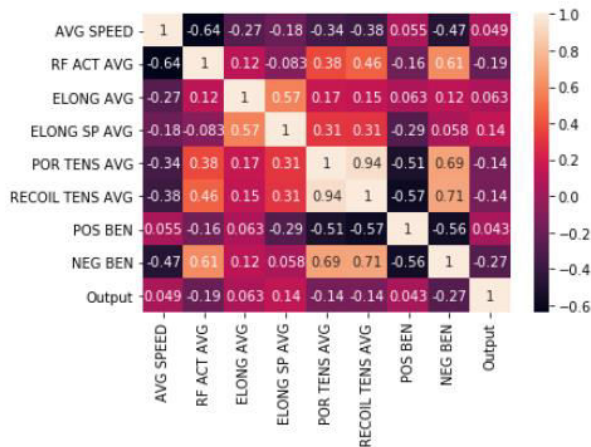


Fig 4: Heat map

We find that some pairs have relationship like

- 1) Negative bending and rolling force,
- 2) Elongation average and Elongation SP average,
- 3) POR Tension and recoil tension,
- 4) Negative bending and recoil tension.

This heat map has shown that along with elongation average, POR tension average some factors like Recoil tension average and Negative bending are also significant.

Heat map along with histogram has confirmed the effect of Negative bending, elongation average, POR tension, recoil tension on the coil break formation.

So now we make a feature significance plot using the python, It will show all the significant factors after computing the data.

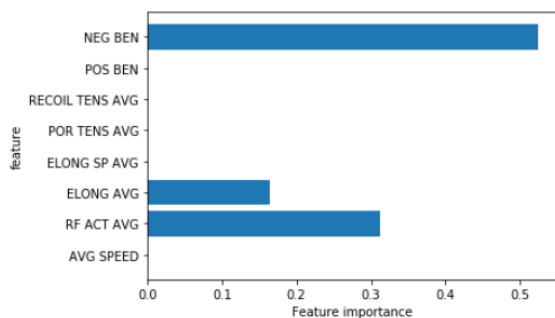


Fig 5: Feature significance

So now we have plot the feature significance for all the inputs. We can see the three inputs Negative bending, Elongation average, rolling force average to be factors which are affecting the output the most. Hence we will further look the feature significance between them.

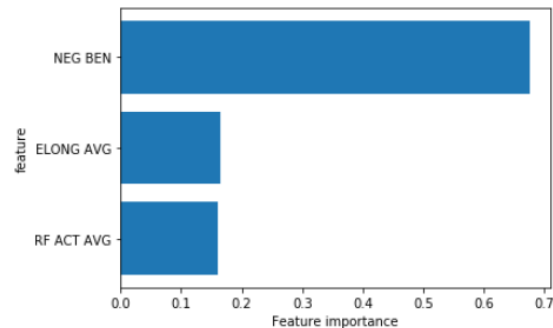


Fig6: Feature significance for important factors

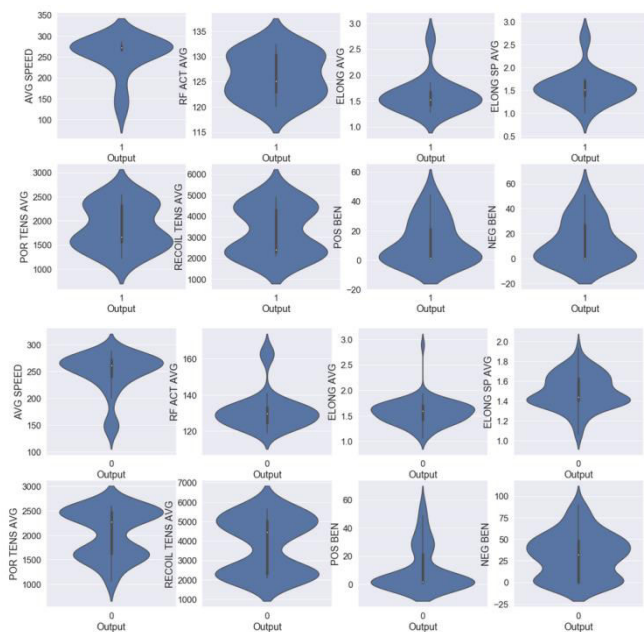
Parameters used for model are

- Number of unique class labels is 10 for the given neural network, 9 inputs and 1 output
- Lambda value for L1-regularization is not done so its value will be 0. This type regularization assigns insignificant value of lambda so as to make the input significance on the outputs similar.
- Lambda value for L2-regularization done so the value is 0.1. Regularization is the technique to make program simpler. This also solves over fitting problem as the loss function is penalized. The L2 regularization forces the inputs to act similarly, it does not make the value zero but close to insignificant.
- Number of epochs means number of passes over the training set is 1000.
- The learning rate for the particular neural network is 0.1. Learning rate is an important parameter that helps to decide how much to change model so as to accommodate the error occurred.
- The momentum constant is 0.1  
Momentum constant is the factor multiplied with the gradient of the previous epoch t-1 to improve learning speed.  
 $w(t) := w(t) - (\text{grad}(t) + \text{alpha} * \text{grad}(t-1))$
- The value of decrease constant is 0.00001

Decrease constant shrinks the learning rate after each epoch using the formula

$$\text{eta} / (1 + \text{epoch} * \text{decrease\_const})$$

- Shuffles training data every epoch if True to prevent circles. For this neural network the shuffle is kept to true. Shuffling data enables that the model is not biased towards a particular series.
- Mini batches means that for efficiency training data is divided into k minibatches. If k=1 it is normal gradient descent learning.
- For this neural network we have set minibatches to 50.

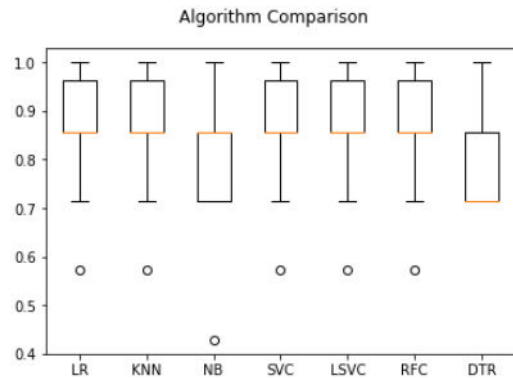


**Fig 7 : Violin plot**

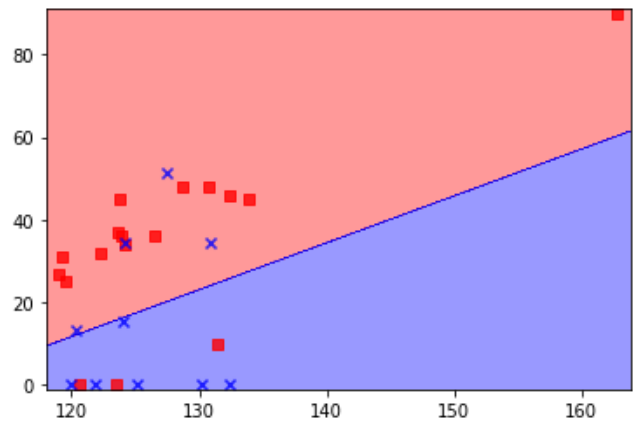
We then wanted to see the distribution of the data points of all the parameters for the entire dataset therefore we plot the violin plots for positive and negative outcome separately.

The violin plots shows quartile ranges properly along with their median and distribution.

We also plot box plot as it along with violin plot will help clarify minute problems. Box plot also works on same idea s violin plot but violin plot is much more detailed as it shows the distribution in form of the shaded area surrounding it. The shaded are around box plot informs the distribution of values.

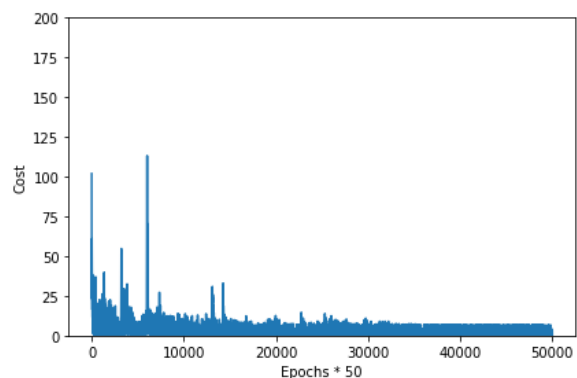


**Fig 8 : Box Plot**



**Fig 9 : Support vector**

The support vector helped to understand the plot very well. Support vector divides the plot in to two parts and are used for binary data and classification type data. Here the plot is divided into two parts namely ‘Blue’ means the area where coil break will not occur and ‘Red’ means area where coil break will occur.



**Fig 10: Cost vs epoch graph**

The accuracy for training graph is 81.43% which is acceptable and as for testing accuracy it increased to 88.89% accuracy. The model is hence successfully done.

## 5. CONCLUSION

Thus we can conclude that after execution of this project the coil breaks which were quite difficult to predict before are now effectively predicted. This will effectively reduce wastage up to a great extent and thus increase the efficiency & availability of the system as well as reducing unnecessary labor fatigue also improving the safety and moral of employees. The company will be going to implement many advance techniques for achieving the above purposes such as provision of cameras for inspection purpose, auto control of loading, bending and other parameters and auto entry of coil in the system. This will enable accurate data and further enhance the predictability.

The design makes the existing model more accurate and reliable. There are multiple ideas presented in this project and one of them is taken into consideration and elaborated thoroughly to the vision of making its idea clearer. The use of simple yet effective artificial neural network reduces pitfalls and makes the system reliable and quick. Its mechanism along with its operation has been properly elucidated along with its advancement from its early design which is attempted to optimize.

## ACKNOWLEDGEMENT

Whenever a work is done successfully, there are many people behind that success. I would like to take this opportunity to sincerely thank people whom I owe a lot. I feel much delighted in expressing deep sense of gratitude to my respected guide **Prof. NIYATI RAUT** for her wholehearted cooperation, encouragement, motivation, valuable suggestions and guidance at every stage of this work leading me to my objectives. I would like to thank **Mr. UDAY MHATRE** (Head of Cluster) and **Mr. SURENDRA CHOUGULE** (Head of Improvement) for their valuable guidance to my project work. Also my grateful thanks to **Mr. Aniket Chatterjee** (Manager, SPM Line) for their valuable knowledge about manufacturing given to me during this training period.

I would also like to thank the whole SPM dept. staff that helped me in solving my difficulties and motivating in my

efforts. I am grateful to Principal **Dr. Arun Kumar** for giving me the opportunity to complete this work.

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