Data Science to Determine Mechanical Properties of Low Carbon Steel During In-Process Inspections

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ABSTRACT

Carbon steel is a widely used category of engineering metal, mainly due to its attractive mechanical and fabrication properties and low cost. The chemical composition, physical parameters, and mechanical properties of carbon steel are maintained as per the specified standards, and local steel should be complied with Sri Lankan Standard 375: 2009. Generally, the chemical composition is tested during melt stages, and mechanical properties are tested for finished products. Since it is necessary to ensure products comply with the standard, mechanical properties are tested during in-process inspections as well. When the results are not within the acceptable range, a considerable amount of production has to be rejected, causing a loss to the manufacturers. If the results of the in-process inspection are instant, it will help make suitable adjustments to process conditions and thereby prevent rejection of products, while reducing quality assurance costs, as well. Therefore, the objective of this study is to predict tensile properties with chemical composition, as input variables, to be used for in-process inspections. Forty mechanical test reports were collected from a steel manufacturing factory for 12 mm diameter, thermo-mechanically treated (TMT) steel bars. Each test report is of 15 samples from the respective batch, and consists of corresponding chemical composition and physical parameters. Multiple linear regression analysis was applied to each batch, using Statistical Package for the Social Sciences (SPSS) software, to predict yield strength (YS), ultimate tensile strength (UTS), elongation at break (EB) with carbon equivalent value (CEQ) and percentage of Sulphur as inputs. Relationships between variables were not significant, even though those relationships can be used to predict tensile properties. The predictions may not be reliable, due to the limited conditions of the study and assumptions made. It is therefore recommended to apply multivariate regression analysis or Artificial Neural Network (ANN) techniques, with other chemical elements, process temperature and water flow rate etc. also as input variables.

KEYWORDS: *Chemical composition, In-process inspection, Low carbon steel, Multiple linear regression analysis, Tensile properties*

1 INTRODUCTION

Plain carbon steel is regarded as a universal engineering metal, due to its many attractive properties during processing as well as usage. Superior strength properties, adaptability to multiple fabrication techniques, amenable to various heat treatments, environmentally favored characteristics, and recyclability are among them. It is also an economically reasonable material. In 2019, the value of the global market size of carbon steel was USD 887.7 billion, and as a reinforcing metal carbon steel finds various structural applications, such as walls, fencing, frames, and pipelines etc. (Grand View Research, 2020). Carbon is the main alloying element that controls the properties of carbon steel, and other elements such as Silicon, Manganese, Sulphur and Phosphorus are also present in it in minor amounts (Pakirappa, 2004). Properties of carbon steel should be maintained within prescribed ranges, according to the specified standards. In Sri Lanka, the chemical composition, physical parameters and mechanical properties of carbon steel should be confirmed with the SLS 375:2009 standard (Sri Lanka

Standard Institution, 2009). The chemical composition of steel is tested during the melting stage, and mechanical properties are tested for manufactured bars. The tensile properties of carbon steel are highly essential components of the tested mechanical properties. YS is regarded as the main property which determines the grade of steel. According to the standard, UTS is also highly important, and the ratio of UTS/YS should be maintained above 1.05. EB is another essential property that should be maintained above 14%. Even though the specified mechanical and physical properties and chemical composition need to comply with standard requirements, approximate values of mechanical properties are sufficient when a quick analysis is done during in-process inspections.

The production of steel is usually held on a 12-hour shift basis, and mechanical properties are tested at the final inspection process, for manufactured cooled bars. In the case of hot rolling mills with manual or semi-automated systems, it is preferable to analyse the same mechanical properties to be tested for finished products, at some frequency, during the production stage itself. This is done in order to ensure that the product quality is maintained for the entire batch; generally, samples are drawn for testing at one-hour intervals. However, the drawn hot samples have to be cooled to room temperature, to be tested for mechanical properties which approximately takes 40–45 minutes. When the test results are found, the mill approximately completes one hour's production period. When the test results are not acceptable, remedial actions need to be taken by quarantining that particular hourly production quantity. If data science is applicable to estimate the essential mechanical properties, immediately after the samples are drawn, it will be beneficial for steel manufacturers as it prevents production losses as well as man power, cost, and the time spent on experiments.

Use of data science techniques in this type of study is found in the literature. Lim (1991) applied multiple linear regression to determine the mechanical properties of two grades of steel, with chemical composition as the input variables. Examples for the use of advanced techniques such as ANN models are also found. To determine the effect of chemical composition and tensile properties on the hardness and the impact toughness of one micro-alloyed steel, ANN networks were implemented (Faizabadi, *et al.*, 2014). In a similar study, to predict tensile properties of austenitic stainless steel, ANN models were applied (Wang *et al.*, 2020) using chemical composition, test temperature and heat treatment as the input variables. Seven data science techniques of Random Forest, Neural Network, Linear regression, K-Nearest Neighbor, Support Vector Machine, Decision Tree, and Ensemble methods were applied (Sandhya *et al.*, 2019) in another study to determine the tensile strength, with carbon percentage, bar diameter, processing temperature and manufacturing technique as the input variables.

The specific purpose of this analysis is to approximate the mechanical properties of final steel products, while they are still in the production progress, using chemical composition as inputs. Since the effect of certain chemical elements is not regarded as independent, carbon equivalent value was considered as one variable, instead of considering individual elements. Advanced techniques of data science such as non-linear regression models or ANN models are preferred for this type of studies. Since the study is an initial step, multiple linear regression analysis was selected as the technique. Thus, the objective of the study was to observe the usefulness of the selected input variables of carbon equivalent value and Sulphur content, to predict the tensile properties of YS, UTS and EB, using multiple linear regression analysis.

2 METHODOLOGY

Forty reports possessing physical parameters and mechanical properties based on the SLS 375:2009 standard were collected from a steel manufacturing factory[1]. The reports were of 12 mm nominal diameter, TMT concrete reinforcing bars of 12RB500 grade, and each test report was of 15 samples from the respective batch. The corresponding chemical composition of each batch was also available in each test report. The readings of the mechanical properties of each batch were averaged before applying for the analysis. The flow rate of water used for the thermo mechanical treatment, inlet

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[1] Test reports of 12 mm nominal diameter, TMT concrete reinforcing bars of grade12RB500, low carbon steel, supplied by a steel manufacturing factory in Sri Lanka were the source of data. Each test report consisted of mechanical properties, physical parameters and chemical composition belonging to 15 samples from the respective batch.

and outlet temperatures of water, billet temperature, and other process parameters were assumed to be the same for all batches.

The data related to 40 batches of samples were analysed with SPSS software using multiple linear regression technique analysis. Percentages of carbon equivalent value and Sulphur were the two independent variables to predict the tensile properties of YS, UTS and EB. Carbon equivalent value is based on all elements of Carbon, Manganese, Chromium, Molumdenum, Vanadium, Nickel and Copper, as per the SLS standard (Sri Lanka Standard Institution, 2009). However, only the Carbon and Manganese amounts are analysed during chemical inspections of this grade of steel, assuming the presence of other elements is insignificant. Table 1 shows the input and output parameters with their relevant statistics used for the analysis.

Table 1. Input and Output Parameters and Their Statistics Used for Multiple Linear Regression Analysis

Parameter	**Unit**	**Maximum**	**Minimum**	**Average**	**Standard Deviation**	**Median**	**Variance**
Input							
CEQ, %	% by weight	0.357	0.282	0.319	0.019	0.32	0.000337
S, %	% by weight	0.04	0.02	0.0293	0.0083	0.03	0.000066
Output							
YS	Nm^{-2} *(10^6)	564	545	555.7	4.2317	556	17.46
UTS	Nm^{-2} * (10^6)	637.6	613.6	627.54	5.9831	627	34.9025
EB	% of original Length	28	22	24.95	1. 2393	25	1.4975

3 RESULTS

The regression equation for YS is given in Eq. (1).

$$YS = 55.524 + 16.49(CEQ\%) - 36.784(S\%) \quad (1)$$

The two graphs of expected values and experimental values of YS are shown in Figure 1.

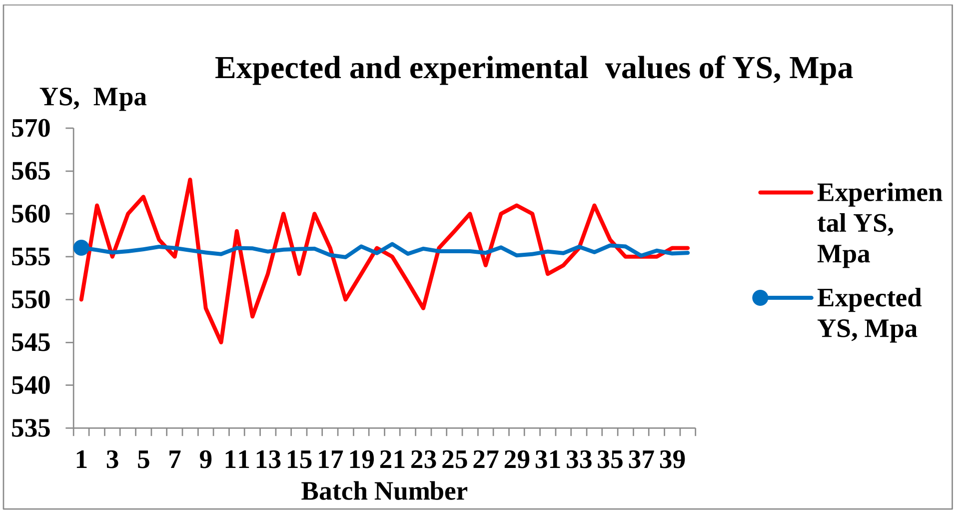

Figure 1. Expected and experimental values of yield strength (YS)

The regression equation for UTS is given by Eq. (2).

$$UTS = 634.566 - 17.213(CEQ\%) - 52.612(S\%) \tag{2}$$

Figure 2 indicates the graphs of expected values and experimental values of UTS.

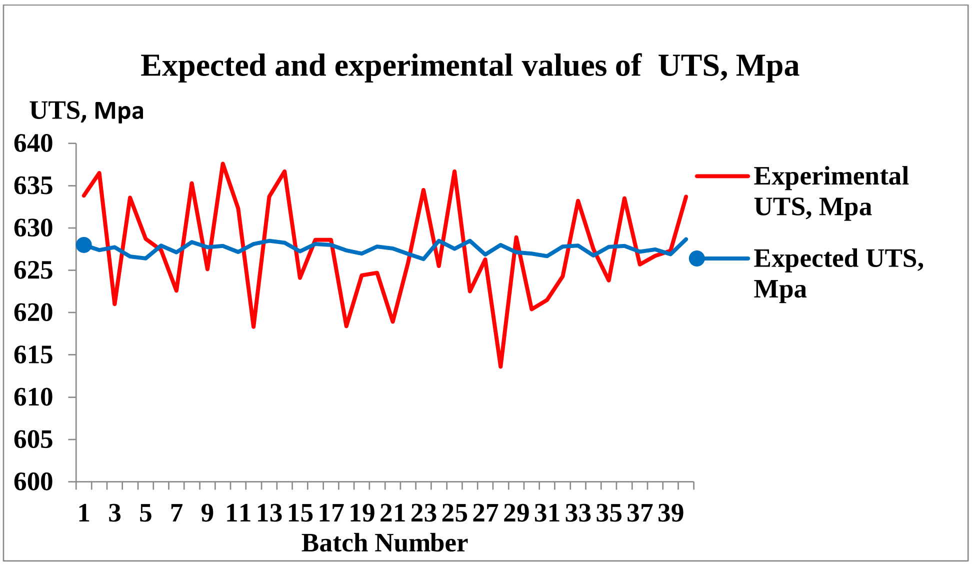

Figure 2. Expected and experimental values of ultimate tensile strength (UTS)

The regression relationship for EB is given by Eq. (3).

$$EB = 26.512 - 5.169(CEQ\%) + 2.893(S\%) \tag{3}$$

Figure 3 shows the expected values and experimental values of EB.

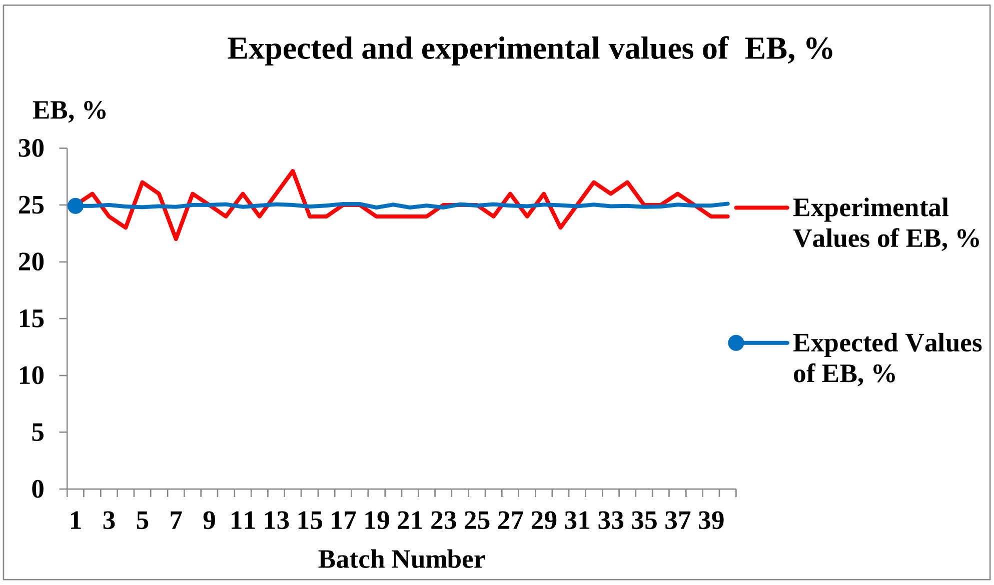

Figure 3. Expected and experimental values of percent elongation at break (EB)

4 DISCUSSION

As per the derived linear relationships for the tensile properties, the obtained P (probability) value in each case was greater than 0.05, and the obtained R^2 values for YS, UTS and EB were 4.8, 5.0 and 5.4, respectively. These details imply that the association of the variables in each relationship is not significant.

The yield strength shows a moderately positive correlation with CEQ%, and highly negative correlations with S%. UTS shows negative correlations with both CEQ%, and S%. Its correlation with CEQ% is moderate while its correlation with S% is considerably high. EB shows a somewhat moderate and negative correlation with CEQ% and a low, positive correlation with S%. There may be other variables which affect these parameters, and the fact that the effects of which were assumed as negligible in the study could be the reasons for the observed correlations.

Since this was an initial attempt to predict the association of the known variables with the expected properties, only average experimental values of properties were applied in order to make the task easy. Additionally, only 40 reports were used, even though a large number of reports are preferable for this sort of analyses. Further, the chemical composition was available only batch-wise; not for the individual samples.

According to the operational manual of semi-automated hot rolling mills, production process conditions such as the flow rate of the water used for the thermo-mechanical treatment, inlet, and outlet temperatures of water, and billet temperature can be varied in the timeline. However, for the analysis, those parameters were considered to be constant and maintained preferably for the process operations.

Even though the major chemical elements, whose presence is regarded as significant, were considered for the evaluation, several other elements which were not considered for this analysis, are also present in this particular steel. Those neglected elements include Cr, Cu, V, Mo and P etc.

This study was focused on only 12 mm nominal diameter bar samples, though there is a preferred range of products available for this grade steel, such as 10 mm, 16 mm, 20 mm, 25 mm, 32 mm, and 40 mm.

This analysis was an initial approach to observe the effectiveness of chemical composition during in-process inspections. The derived relationships can be used to approximate the tensile properties, provided the other process conditions are not varied throughout the entire process, which may not be generally plausible. Therefore, for more reliable relationships for the expected properties, actual variation of other process conditions must be considered during the analyses.

5 CONCLUSION

Data science techniques are used nowadays to predict the details of material science techniques. Therefore, mechanical properties obtained by conventional experimental methods can be predicted through the application of proper data science models. The accuracy of data science-based approaches will be dependent on the input of sufficient accurate details.

This study was an initial attempt to analyse the possibility of applying the available data to obtain the results of mechanical tests, done for finished products of a selected low carbon steel, using linear regression models. The study was conducted under certain limitations and assumptions. The obtained results will be helpful to predict the properties, provided all other process conditions are not changed throughout the entire production process. Therefore, to obtain more reliable results, the study needs to be redesigned with more input variables of actual process conditions.

6 RECOMMENDATIONS

In future studies, models developed with more input variables are recommended, expecting improved accuracy. Contents of other available chemical elements, process parameters, and heat treatment conditions can be applied as other inputs. Other preferable ranges of products with different bar diameters may be considered with a higher number of test records. Another suggestion is to use chemical element contents obtained sample-wise, instead of the contents obtained batch-wise.

The analysis can also be focused on non-linear multivariate relationships or more advanced techniques, such as ANN models and grey theory models etc.

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