Modeling Mechanical Properties of low carbon hot rolled steels

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Abstract:

Steel is the most important material and it has several applications, and positions second to cement in its consumption in the world. The mechanical properties of steels are very important and vary significantly due to heat treatment, mechanical treatment, processing and alloying elements. The relationships between these parameters are complex, and nonlinear in nature. An artificial neural networks (ANN) model has been used for the prediction of mechanical properties of low alloy steels. The input parameters of the model consist of alloy composition (Al, Al soluble, C, Cr, Cu, Mn, Mo, Nb, Ni, P, S, Si, Ti, V and Nitrogen in ppm) and process parameters (coil target temperature, finish rolling temperature) and the outputs are ultimate tensile strength, yield strength, and percentage elongation. The model can be used to calculate properties of low alloy steels as a function of alloy composition and process parameters at new instances. The influence of inputs on properties of steels is simulated using the model. The results are in agreement with existing experimental knowledge. The developed model can be used as a guide for further alloy development.

Keywords: Artificial Neural Networks, Low carbon steels, Mechanical properties, Process parameters.

1 Introduction

Microstructure of steels determines the properties of steels and the microstructural features depend on alloying elements, process parameters, and heat treatment variables. As the relationships between these are nonlinear and complex in nature, it is difficult to develop them in the form of conventional mathematical equations [1-3]. Linear regression techniques are not suitable for accurate modelling of steels data with noise which is typically the case. Regression analysis to model non-linear data necessitates the use of an equation to attempt to transform the data into a linear form. This represents an approximation that inevitably introduces a significant degree of error. Similarly, it is not easy to use statistical methods to relate multiple inputs to multiple outputs. The method using Artificial Neural Networks (ANN), on the other hand, has been identified as a suitable way for overcoming these difficulties [4-7]. ANN is mathematical models and algorithms that imitate certain aspects of the information-

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processing and knowledge-gathering methods of the human nervous system. Although several network architectures and training algorithms are available, the feed-forward neural network with the back-propagation (BP) learning algorithm is more commonly used. Therefore, within the last decade, the application of neural networks in the materials science research has steadily increased. A number of reviews carried out recently have identified the application of neural networks to a diverse range of materials science applications[4]. The objectives of the present work are to investigate its suitability for modeling complex hot rolled steel system, to predict properties for unseen data, and to examine the effect of individual input variables on the output parameters while keeping other variables constant.

Several ANN architectures and training algorithms are available; the feed-forward neural network (FFNN) with the back-propagation (BP) learning algorithm is more commonly used. The conceptual basis of back-propagation was first presented in 1974 by Paul Werbos then independently reinvented by David Parker in 1982, and presented to a wide readership in 1986 by Rumelhart and McClelland [8-12]. Back propagation is a tremendous step forward compared to its predecessor, the perceptron. The power of back-propagation lies in its ability to train hidden layers and their bye escape the restricted capabilities of single layer networks. When two or more layers of weights are adjusted, the network has hidden layers of processing units. Each hidden layer acts as a layer of "feature detectors"-units that responds to specific features in the input pattern. These feature detectors organize as learning takes place, and are developed in such a way that they accomplish the specific learning task presented to the network[10]. Thus, a fundamental step toward solving pattern recognition problems has been taken with back-propagation. At present, the most common type of ANN used in materials science is FFNN with back propagation learning algorithm.

2 Experimental data details:

Finish rolling temperature and coil target temperature apart from chemical composition play an important role in the mechanical properties hot rolled steel strip. The hot rolled steel strip data of three days has been collected from an industry and modelled to study the effect of the said temperatures on mechanical properties. The data consists of chemical composition (Al, Al soluble, C, Cr, Cu, Mn, Mo, Nb, Ni, P, S, Si, Ti, V and Nitrogen in ppm, i.e. 15 inputs), finish rolling temperature (FRT), coil target temperature (CTT), and respective mechanical properties, namely, YS, UTS and EL. The range of the hot rolled steel strip data used for the present study is shown in the Table 1. Total 435 data sets with 17 input parameters were available and 335 sets were used for training. The best results were achieved at a learning rate of 0.7 and momentum rate of 0.6 with 2 hidden layers consisting of 34 hidden neurons in each layer. The predicted results of optimum trained NN model are within 4% of experimental values in most of the cases.

Table 1 The range of the Hot rolled steel strip data

Comp.	Al	ALS	C	Cr	Cu	Mn	Mo	N	Nb	Ni
Min.	0.021	0.02	0.02	0.014	0.005	0.17	0.001	26	0	0.008
Max.	0.065	0.063	0.06	0.039	0.012	0.38	0.003	58	0.004	0.0179

Comp.	P	S	Si	Ti	V	FRT	CTT	Mechanical Properties		
								LYS	UTS	EL
Min.	0.007	0.003	0.004	0	0.001	850.23	570	242	317	34
Max.	0.024	0.02	0.028	0.003	0.002	901.14	650	338	397	46

3 Model development and Graphical user interface design

A graphical model plays a crucial role in easy understanding and analysis of any complex systems. The present model development involves in two phases, training phase and representation of results phase. Object oriented programming language Java has been used to develop the training and representation of results phases. Training phase consists of collection of the training data, normalizing the data, selection of inputs and outputs, selection of neural networks parameters. In the training phase each of the systems are trained with various configurations and an optimum configuration is chosen which, satisfies the permissible error and minimal usage of the system resources. The final configuration is saved to files. Thus generated data is passed on to the representation phase for the further processing. The training phase takes a considerable amount of time for each process and often requires a trial and error mode of selection of hidden layers and the number of hidden neurons and the choice of learning rate, momentum rate and permissible error level is dependent on the complexity as well as the precision requirements of the system. The training phase is coded in such a manner, that the application module can be used in various technical applications and hence requires no knowledge of metallurgy to understand the software source.

Considering the time constraints and the added uncertainty in the choice of the configuration, the content generation phase is separated from the content representation. In addition, the representation phase includes the analysis of the system, which forces extensive knowledge in metallurgy; henceforth the layered structure of the isolation of the content generation and the representation is an objectified approach satisfies the principles of software development.

The required models are trained during the training phase and the network description files, the weight file along with the other required files are placed in a proper location accessible by the model. The representation phase is where model is tested for its precision, sensitivity of various inputs and outputs are determined and some inputs are plotted against the outputs and to determine outputs for the custom inputs. The model is represented as an application where each of the plots or the features is presented in separate tabs. Whenever the basic model is changed the new serialized model, which has the trained weights, is read as the current model and this will update all the plots in the tabs in turn. For the Sensitivity analysis of the input/output parameters of the lower end is send to the model to retrieve the outputs and again the inputs/output parameters of the upper end is passed onto the model to retrieve the upper limits of the outputs. From these the slope is determined and plotted in the form of blocks.

Various systems are currently under study, while these can be categorized, there are primarily two types of categories, and one is based on the type of metal being studied and other by the type of the process being used to study the system. Hence the representation is done in an application frame, which constitutes a menu bar, tool bar, status bar in addition to the actual plots for switching between various models and to have inline status help. The use of technical terms is discouraged to make the model understandable even for non-metallurgists who are not experts in process concepts or the domain knowledge. On the base of the designed FFNN model, various graphical user interfaces were created for a better and easy understanding of the system.

4 Results and Discussions

4.1 FFNN model Predictions with Test data

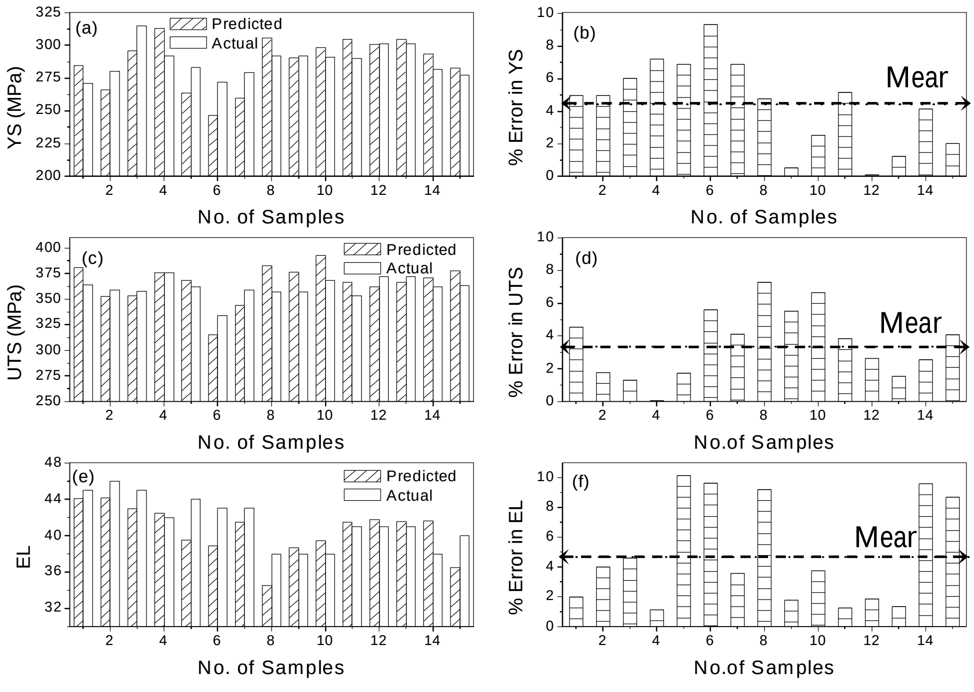

Fig. 1. FFNN model prediction for test data of Hot rolled steel strip

Total data sets available for FFNN Model training are 435. First 335 data sets have been used for training and remaining 100 data sets, which are randomly chosen from the total data sets, is used for testing. As it is difficult to represent the complete predictions, the predictions of randomly selected fifteen test data sets are shown in Fig.1. The comparison between actual and predicted properties for the 15 testing data sets of hot rolled steel strips is shown in

Fig. 1. It was observed that most of the outputs predicted by the model are within 5% of the error band (indicated in (b), (d) & (f)). For the testing data never seen by the model, the FFNN Model gives a reasonably accurate prediction. The mean percentage error in the case of YS, EL and hardness are 4.44, 3.54 and 4.84 respectively. In most of the cases the deviations are less than 5%.

4.2 *Hypothetical Alloys for FRT and CTT*

Sensitivity analysis studies the effects of parameter variations on the behavior of complex systems. The concept of sensitivity analysis can be extended to all essential parameters of continuous, discrete, or continuous-discrete systems. The sensitivity analysis of the trained FFNN models evolved and its application is explained in the earlier [1-3, 13-15]. The effect of chemical composition and two process parameters namely coil target temperature, finish rolling temperature individually and together on mechanical properties has been presented in the case of low carbon hot rolled steel strip. In the steels studied so far the chemical composition and heat treatment variable on properties are considered [1-3, 16-18]. However, the mechanical properties also depend on the process parameters like coil target temperature, finish rolling temperature and the forces applied during rolling of the hot rolled steel strip. In the present section, the effect of coil target temperature and finish rolling temperature variations on mechanical properties of hot roll steel strip are studied. Fig. 2 shows the variations of coil target temperature and finish rolling temperature simultaneously and their effect on mechanical properties. The figure indicates that the influence of finish roll temperature on the mechanical properties is more complex than that with coil target temperature. This is expected as the finish roll temperature (ranging between 850-910^{o}C) influences a number of parameters such as volume fraction of proeutectoid ferrite, grain size of ferrite and the texture developed during rolling, precipitation of various carbides, etc. While the coil target temperature being in the range of 570-650^{o}C, is much below the eutectoid temperature and hence only brings in smaller variation in microstructure and hence smaller variation in the properties. The effect of combined variation of finish rolling temperature and coil target temperature on mechanical properties is presented in Fig. 3. Table 2 shows the two temperatures for one data set and the respective properties and the model predicted properties with different input variations. The model predictions of test data are well within 5%.

Increase in coil target temperature increases strength around 605^{o}C and then the grain size increases with further increase in temperature and the corresponding strength decreases and the respective rise in ductility. The grain growth restriction will takes place at higher coil target temperature and there-by-there is no change in the strength and ductility. The model predicted this phenomenon very well. As finish rolling temperature increases initially strength increases owing to plastic deformation and very little amount of precipitation. At the same time elongation falls drastically. This happens for increase in precipitate later with increase in temperature grain growth will takes place, which increases ductility and decreases strength. And at 890^{o}C, strength decreases at lower value for larger grain size. Then ductility falls due to the starting of precipitation again. Thereafter precipitation and grain growth takes place simultaneously increase at a same time which results increase in strength and ductility. Table 2 shows the model predictions are well in agreement with the actual values.

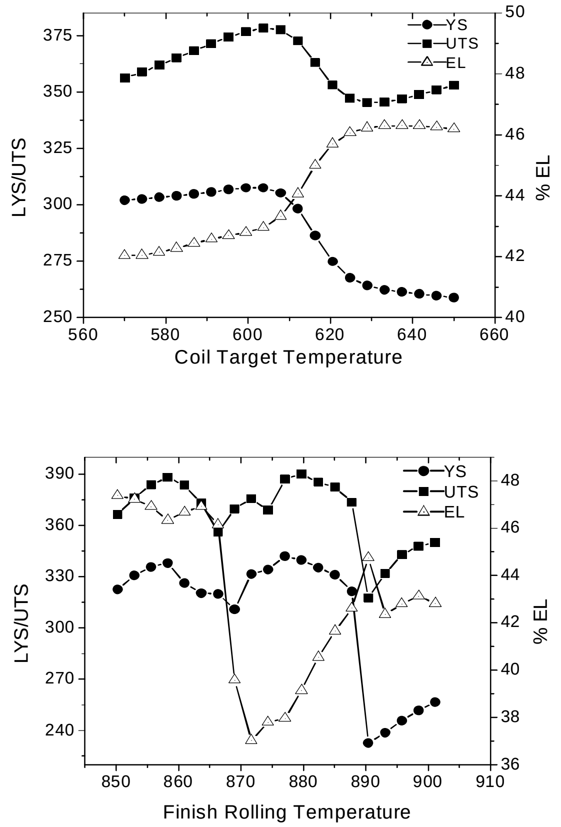

Fig 2 Effect of the variation of Finish Rolling Temperature and coil target temperature on Mechanical properties

Table 2 Comparison of actual and predicted properties of hot rolled steel strip with respective hypothetical alloys

System	LYS	UTS	EL
Actual	302	356	42
HA based on Finish Rolling Temperature (867.95^{o}C)	313	365	41.8
HA based on Coil Target Temperature (570^{o}C)	303	358	42.5

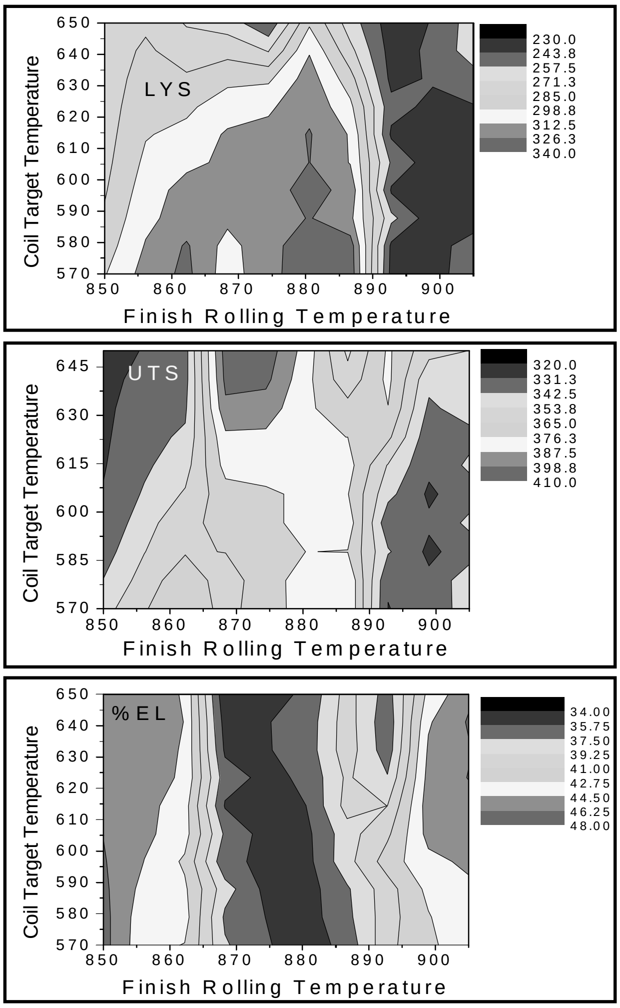

Fig 3 Combined effect of the variation of coil target temperature (a) and finish rolling temperature (b) on Mechanical properties

5 CONCLUSIONS

Neural networks model for prediction and analysis of the hot rolled steel strip data has been developed. The results demonstrated that the model can be used to examine the effects of individual inputs (Coil target temperature and finish rolling temperature) on the output parameters (mechanical properties), which is incredibly difficult to do experimentally. The present model will be helpful in reducing the experiments required for new alloys with desired properties. The user-friendly screens of the present model can make even a layman use it conveniently without the knowledge of any programming.

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