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Artificial Neural Network Modeling the Tensile Strength of Hot Strip Mill Products

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In this study, the effects of chemical composition and process parameters on the tensile strength of hot strip mill products were modeled by Artificial Neural Network (ANN). A good performance of network was achieved when compared with the experimental data taken from Mobarakeh Steel Company (MSC). Moreover, the relative importance of each input variable was evaluated by sensitivity analysis. The results are evaluated based on metallurgical phenomena of steels. Therefore, it is proposed that, this model can be employed as a guide to predict the final mechanical properties of commercial low carbon steel products.

KEY WORDS: artificial neural network (ANN); modeling; hot strip mill; tensile strength; chemical composition; processing parameter.

1. Introduction

Low alloy steels are the most demanding materials that are used in industrial processes such as hot stripping. In this process the cast steel is severely deformed into strip and at the same time the refinement of structure brings about a simultaneous improvement in strength and toughness.[1] The effects of chemical composition on these properties are an important parameter as well as thermomechanical processing features such as temperature and final dimensions.[2]

The additions of some alloying elements affect ferrite transformation and thus control the amount of phases present in the final matrix. The presence of microalloying elements generally control the grain size and provide precipitation strengthening and have a significant impact on the strength.[1] The evaluation of these mechanisms which are considered as metallurgical phenomena can be very complicated. Consequently, the overall effects of these features can have an effect on rolling design and therefore too many experimental trials are needed to achieve ideal tolerances. Trial and error approach increases the cost and production time, therefore the best design is the one without implementing any experimental tests.

In this paper the effects of chemical composition and processing parameters (23 variables) on the tensile strength of hot strip mill products were modeled using Artificial Neural Network (ANN) method. This model also capable to explore the effect of each input parameter which this task is difficult or sometimes impossible to do in experimental. The method and variables are introduced below.

2. Method

2.1. Artificial Neural Network

ANN is a parameterize model used for empirical regression and classification and its flexibility makes it able to discover more complex behaviors than traditional statistical models.[2] Unlike traditional models which a specified relationship must be chosen before analysis, ANN is a general regression method and trained on a set of examples of input and output data.[3] The result of this training is a set of weights that by combining with specified functions, represents the trend between inputs and outputs. Therefore, the training is a search procedure in the weights space for the best nonlinear representation of data behavior. Once the network trained and the relationship determined estimation of new outputs for given inputs is straightforward. A feed-forward network composes of an input layer, one output layer and hidden layer(s) which the number of neurons in hidden layer(s) only, is in our control and indicates the model complexity. Arrangement of layers and units in an ANN called architecture.[4] **Figure 1** sketches schematic architecture of a feed forward ANN model. In each layer, units receive their input from previous layer's units and send their output to units in the following layer. Output of each hidden unit is the transfer function response to the weighted sum of its inputs. In this work, the nonlinear hyperbolic tangent transfer function and linear transfer function was used as hidden unit and output unit respectively.

2.2. Network Database

Performance of an ANN model depends on experimental data to discover the underlying behavior. Annual products data report of Isfahan Mobarakeh Steel Company (MSC) for hot striping mill were used for this modeling, which

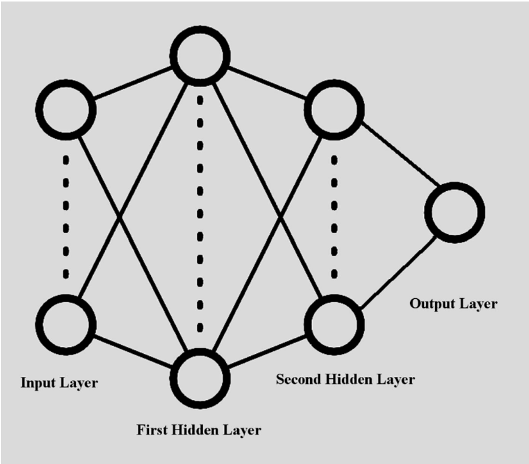

Fig. 1. Schematic architecture of neural network.

input parameters consisted of:
(i) Final thickness
(ii) Initial and final weight
(iii) Initial width
(iv) Reheating furnace temperature, roughing temperature, finishing temperature and coiling temperature
(v) The chemical composition, consisting 14 different elements
(vi) The carbon equivalent according to the following formula:

$$\mathrm{Ceq}=\mathrm{C}+\mathrm{Si}/25+(\mathrm{Mn}+\mathrm{Cr})/16+(\mathrm{Cr}+\mathrm{Ni}+\mathrm{Mo})/20+\mathrm{V}/15 \quad \text{..........(1)}$$

where elements are expressed in weight percent.

About 70234 examples each consisting of corresponding input and output were available for modeling. Some further information about the variables are given in **Table 1**. These examples were normalized so that they had zero mean and unity standard deviation before computations.

2.3. Bayesian Regularization for Neural Network

Conventional performance function of neural network which optimization applied on it, has general form of:

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \quad \text{........(2)}$$

where *mse* is mean of squared error. If the performance function is changed by adding a term that contains mean of squared weights (*msw*), yield:

$$msereg=\gamma mse+(1-\gamma)msw \quad \text{..........(3)}$$

Where γ is the performance ratio, and

$$msw=\frac{1}{n}\sum_{j=1}^{n} w_j^2 \quad \text{..........(4)}$$

Using this performance function leads to smaller network weights and biases, which makes the network response to be smoother and less likely to over-fit.[5] The main remaining problem is to find the ideal value for the performance ratio. Choosing too large ratio increases over-fitting likelihood and too small ratio prevents network to fit adequately the training data.[6]

To find out the best regularization, Mackay[6] in his Bayesian framework suggests, assuming the weights and biases as random variables with specified distributions and related the regularization parameters to these distributions. Another approach suggested by Foresee[7] in which the Levenberg–Marquardt method employed for training. Present work applied this approach.

Table 1. Input and output parameter informations.

	Variables	min	max	mean	SD
Inputs	Final Thickness(mm)	1.5	16	5.244903	3.155532
	Final Weight(kg)	5097	28030	18502.91	3214.769
	Initial Weight(kg)	5202	28660	18874.26	3264.811
	Initial Width(mm)	650	1850	1277.022	205.7713
	Furnace Temp(°C)	1164	1296	1229.77	23.4407
	Roughing Temp(°C)	932	1122	1058.281	14.00645
	Finishing Temp(°C)	782	960	881.1131	23.32006
	Coiling Temp(°C)	517	729	610.5108	18.02052
	C (wt %)	0.03	0.21	0.126968	0.02545
	Si (wt %)	0	0.347	0.070235	0.084277
	Mn (wt %)	0.175	1.38	0.658662	0.206133
	P (wt %)	0.001	0.026	0.006786	0.002377
	S (wt %)	0	0.02	0.008637	0.002686
	Cu (wt %)	0	0.264	0.029318	0.011597
	Al (wt %)	0.007	0.093	0.045926	0.010957
	N (ppm)	15	90	39.784	9.221
	Nb (wt %)	0	0.06	0.004854	0.009032
	V (wt %)	0	0.043	0.003378	0.001607
	Ti (wt %)	0	0.042	0.001654	0.002318
	Mo (wt %)	0	0.022	0.003654	0.004104
	Cr (wt %)	0.001	0.194	0.011992	0.008007
	Ni (wt %)	0.016	0.243	0.028205	0.004679
	C_{eq} (wt %)	0.068032	0.437799	0.2443845	0.0534388
Output	Strength (MPa)	299	659	444.64	48.68

SD: Standard Deviation C_{eq}: Carbon Equivalent

2.4. Network Training

ANN with Bayesian Regularization has good predictive accuracy (generalization). Furthermore according to Mackay[6] specified network architecture in Bayesian framework doesn't need of test data to adjust its complexity. Therefore, 90% of total data set was dedicated for training and remaining data to evaluate generalization on unseen data of the best network. Several architectures were examined for finding the best network. The network architecture was started with a few hidden units in a single hidden layer and as the number of hidden units increased the performance of model getting better. This trend was reasonable because according to (Eq. (3)) when the number of the training data is raised, the number of the weights must also increase for better control of performance. Furthermore, with equal number of hidden units two layer networks (which have more weights) reveal better performance than single layer networks. Finally, the best network architecture was determined with 23–60–50–1 architecture.

Bayesian regularization controls the complexity of the network and prevents the network to over-fit; therefore with this algorithm the need to do guesswork for finding the best network architecture is much less. Training was stopped when the performance criteria (*i.e. mse*, *msw* and performance ratio) were stabled, which is a good signal for this algorithm. This training task was computational demanding and took more than 55 h on a dual 3.2 GHz processor with 2 gigabyte memories.

2.5. Calculation of the Weights of Individual Input Variable

Extracting effective information from a neural network model is not as easy as conventional linear regression because the discovered relationships with neural network are much more complicated. However when the output layer only consists of one neuron the dependency of output variable on inputs is same as network dependency to input parameters. On the other hand, in feed-forward networks the path which the effects of the input parameters carried is straightforward from input layer to output layer. Therefore, the weights which fan out the input units can be considered as their significance, like the impact of inputs on output in linear models. The relative importance of individual input variable on output variable can be expressed as[8]:

$$I=\frac{\sum_{j=1}^{S}\left|w_{ji}\right|}{\sum_{i=1}^{N}\sum_{j=1}^{S}\left|w_{ji}\right|} \quad ....(5)$$

Where w_{ji} is the connection weight from i input neuron to j hidden neuron, N, S are the number of input parameters and hidden neurons, respectively.

3. Results and Discussion

3.1. Model Performance

Figure 2 shows the model generalization by scatter diagrams of predicted values *versus* measured values for both training (a) and test data (b). This figure shows the correlation coefficients of both training and testing sets are close to unity which indicates that results are in good agreement with experimental data.

Optimum weights of the network model are available for reproducibility purposes through this link (http://www.docstoc.com/docs/5549898/Optimum-Weights-of-Network-Related-to-my-ISIJ-Article).

3.2. Sensitivity Analysis

Figure 3 shows the importance of input variable relevancies on tensile strength which were analyzed by the method mentioned in Sec. 2.5. Figure 3 shows that silicon, carbon, manganese, copper, nickel and chromium give a large contribution to the strength. Moreover, microalloy elements such as niobium, vanadium and titanium, though less than other elements, have a similar effect of strength. Among the processing features, the width and thickness of the strip revealed remarkable influence on tensile strength.

The depicting effect of mentioned factors and their interactions with one another, two parameters were altered at a time and other parameters were kept on their mean values which are tabulated in Table 1.

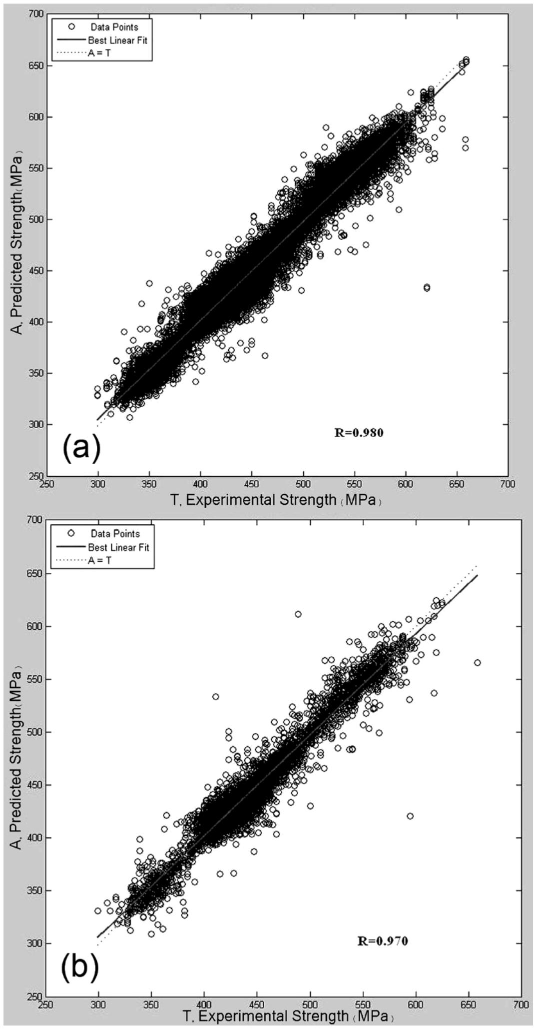

Fig. 2. Behavior of model on (a) training data (b) test data.

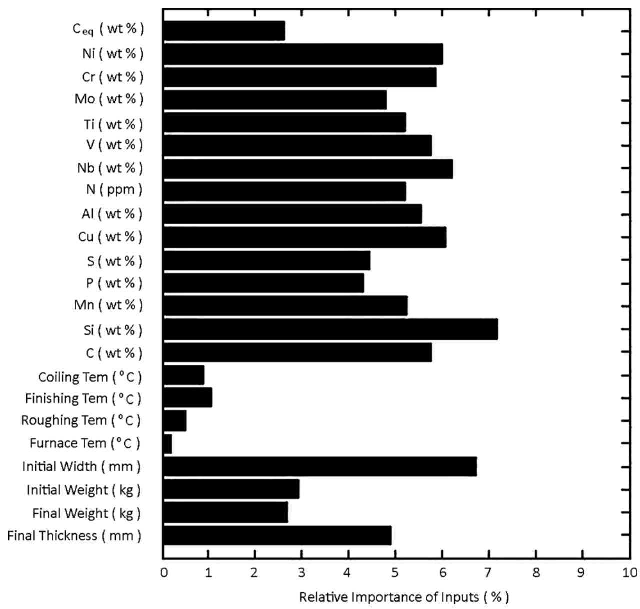

Fig. 3. Relative importance of inputs.

3.3. Effect of Chemical Composition

Carbon has a major effect on steel properties and increases the strength by interstitial solid solution strengthening. This effect is more pronounced in ferritic steels. In fer-

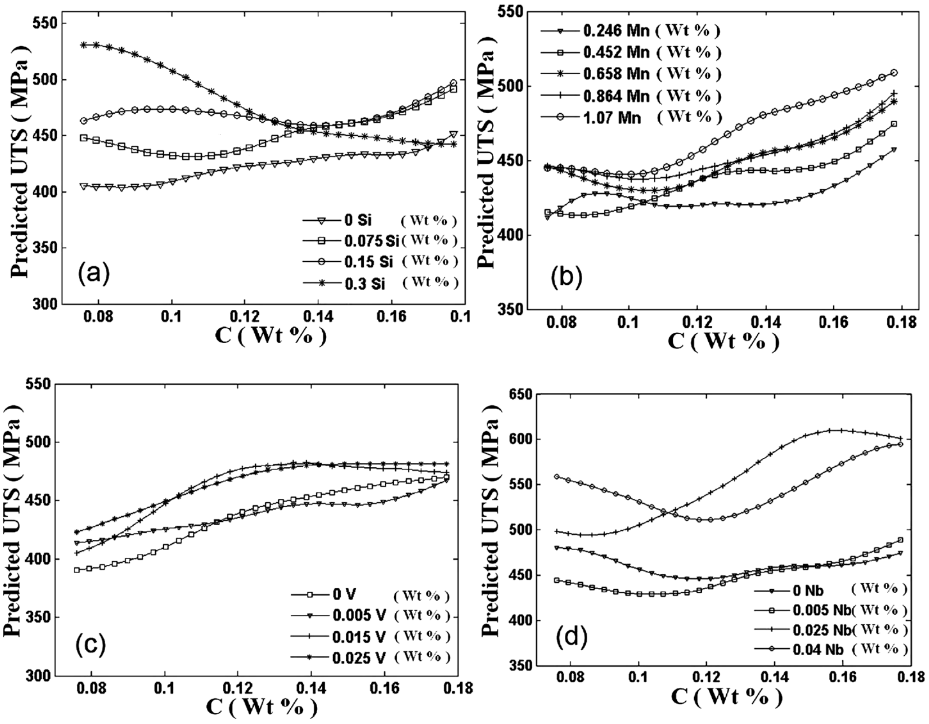

Fig. 4. Carbon concentration effect in combination with (a) silicon, (b) manganese, (c) vanadium, (d) niobium.

ritic–pearlitic steels, the carbon content raises pearlite volume which in turn leads to the increase of alloy strength.[1)] Silicon is one of the principal deoxidizers used in steelmaking, **Figure 4**(a) shows silicon effect which enhances the strength by suppressing precipitation of cementite from austenite. Thus carbon remains in austenite for subsequent strengthening.[9)] The effect is more pronounced in steels with lower carbon concentration because silicon dissolves in the ferrite. Manganese promotes stronger steels by stabilizing austenite and solid solution strengthening.[1)] The increase in strength is dependent upon the carbon content as is shown in Fig. 4(b).

However the concentration of microalloy elements is low, they have a significant influence on several stages of rolling. Unlike alloying elements that alter the structure of iron, microalloy elements have a great affinity to combine with other elements such as carbon and nitrogen. This results in precipitation of several secondary phases.[10)] Vanadium compounds hardly remain in austenite and when transformed into ferrite, precipitate in the matrix.[11)] The grain refining ability of vanadium is lower than niobium (Figs. 4(c) and 4(d)). On the other hand, as the most effective microalloy, Niobium contributes towards the prevention of austenite grain coarsening during reheating period and retards the recrystallization temperature during rolling. Niobium also reduces the transformation temperature by solute drag effect.[1,11)] Figure 4(d) shows that the addition of 0.025 wt% Nb, improves tensile strength more than that of 0.04 wt%. For instance in a steel with a carbon content of 0.15 wt%, addition of 0.025% Nb increases tensile strength by 150 MPa. At the same time, the addition of the same amount of vanadium increases the strength by up to 50 MPa. **Figures 5**(a) and 5(b) show that manganese, niobium and carbon strongly depend on one another. The minimum and maximum values of strength, according to Fig. 5, are when niobium reaches to about 0.012 and 0.025 wt% respectively.

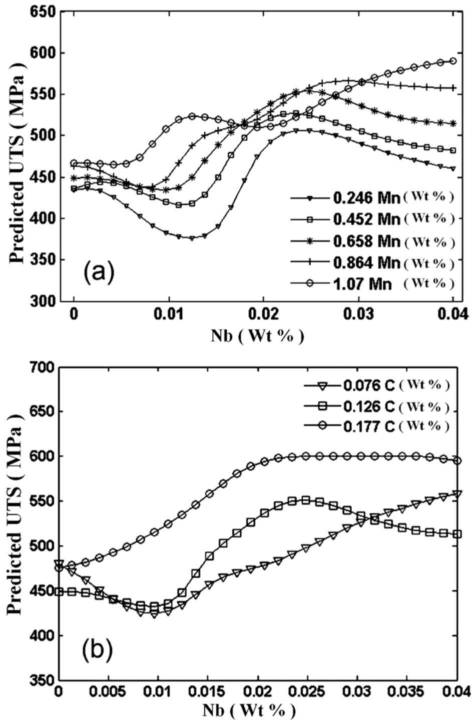

Fig. 5. Niobium concentration effect in combination with altering (a) manganese and (b) carbon.

3.4. Effect of Process Parameters

Figure 6(a), displays the effect of strip thickness *versus* manganese content on the final tensile strength. The results indicate a drop in tensile strength when final thickness is increased. This can be attributed to lower cooling rate of thicker strips. Therefore, coarsening takes place and the

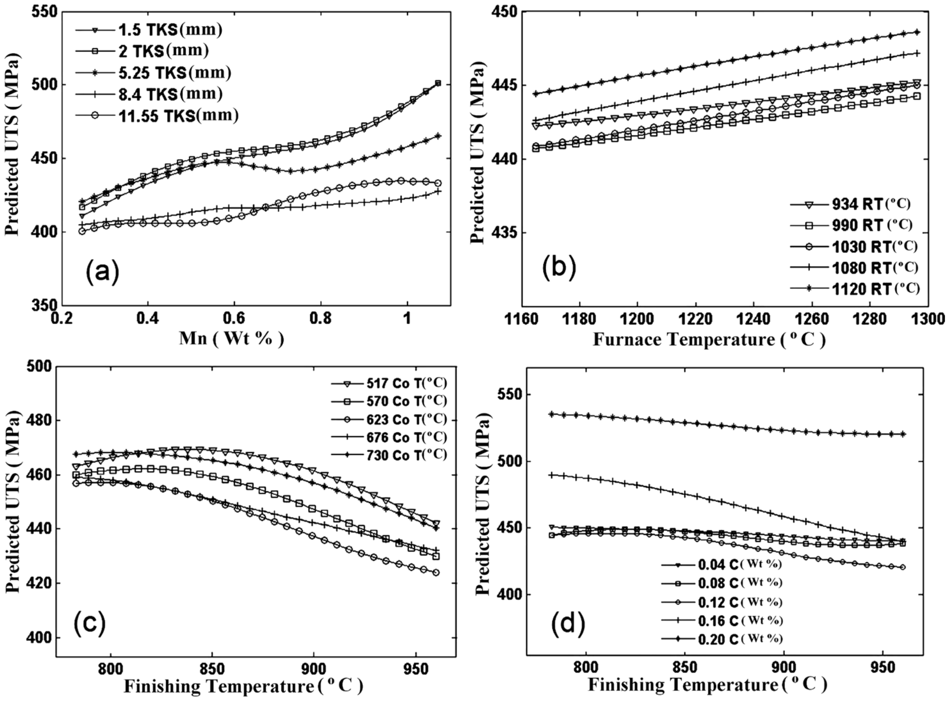

Fig. 6. Interaction of processing feature (a) final thickness and manganese concentration, (b) furnace and roughing temperature, (c) finishing and coiling temperature, (d) finishing temperature and carbon concentration.

tensile strength decreases.[1] This figure also illustrates the more influential effects of manganese on thinner strips. Also, Fig. 6(b), points to the effects of reheating and roughing temperatures on strength. Increasing reheating temperature slightly enhances the tensile strength. This is because, precipitates that influence the microstructure of steel should come from solid solution of the steel.[12] Figure 6(c) shows predicted tensile dependency, to the finishing and coiling temperatures. It shows that by decreasing finishing temperature, the final tensile strength increases. Inter-pass recrystallization and grain growth prevention my causes this effect.[13] It also implies that lower coiling temperature, raises the tensile strength of the alloy. The influence of temperatures on tensile strength is not significant when compared with that of chemical composition (in specified ranges). Figure 6(d) reveals the significance of finishing temperature verses the carbon concentration on tensile strength. This finding is consistent with the results in Fig. 3.

4. Conclusions

(1) The effects of chemical composition and process variables on the tensile strength of hot strip mill products were modeled by Artificial Neural Network (ANN). The developed network showed good performance and network results were in good agreement with experimental data taken from Mobarakeh Steel Company (MSC) database.

(2) The relative importance of each input variable was evaluated by sensitivity analysis. The influence of chemical composition on final tensile strength is much more pronounced than process parameters.

(3) The results show the effects of the parameters are too complex to model with a simple linear regression technique. The developed ANN model can be used as a guide to control the final mechanical properties of commercial carbon steel products.

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