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Modeling the yield strength of hot strip low carbon steels by artificial neural network

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ABSTRACT

The influences of chemical composition and process features on the yield strength of hot strip steels were modeled by artificial neural network (ANN). The developed model revealed good agreement with experimental data taken from Mobarakeh Steel Company (MSC). The results for the several input parameters are shown and compared with metallurgical phenomena such as elemental effects or strengthening mechanisms. The developed model can be used as a quantitative guide to control the final mechanical properties of commercial low carbon steel products.

1. Introduction

Low carbon strip steels occupy large portion of annual steel production. They have a range of yield strengths which is suitable for different applications [1]. Hot stripping is a severe plastic deformation which is applied on cast steels for a variety of shapes and sizes. The process enhances the properties of steels by several metallurgical mechanisms which take place in different parts of the hot strip mill. These include:

1. Austenitization, dissolution of microalloy compounds and homogenization of the chemical segregation in the reheating furnace.
2. Deformation and reduction of reheated slab to intermediate thickness which is accompanied with recrystallization, grain growth and precipitation of alloying and microalloy elements in roughing and finishing mills.
3. Phase transformation and precipitation during cooling and decreasing the heat to room temperature [2,3].

These mechanisms depend on steel composition and process features, therefore, estimating the yield strength from these parameters is desirable from engineering view point. Traditionally, setting the tolerances is carried out by making several samples and checking the final results by trial and error approach. Generally, these procedures are expensive and time-consuming. Also, developing a physical model with such a complexity is extremely difficult. For these reasons, a model is introduced based upon a neural network method. This model is capable of understand very complex and unknown relationships between inputs and output data. Furthermore, the model can explore the effect of the individual input on output which can be extremely difficult in the experimental tasks.

Achieved model can be used as a quantitative tool to predict the final YS of these commercial low carbon steels with different of input variables. This is desirable from designing and engineering point of view. Moreover analysis of the effect of input parameters on results may leads to design new steels with different input parameters.

2. Method

2.1. Artificial neural networks

A neural network is an interconnected network of a set of simple processing units which are connected by a set of connections called “weights”. They can learn the given information by a set of examples and transfer them to their structure. The method which is inspired from studying the human brain, is capable of recognizing complex patterns of the training data and can be applied to regression and classification tasks. The training is an optimization procedure by finding a set of weights which combined with processing units, describes the data pattern. There are several advantages in this method. Firstly, there is no need to choose the behavior of the model in advance. Secondly, its need to train data,

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does not grow as fast as other conventional regression methods and therefore, growing the complexity and dimensionality of the problem does not need any further data. The general structure (called architecture) in this network consists of three types of layers, input, hidden and output layers. The number of units in input and output layers are dictated by the problem, but the number of hidden units which control the complexity of the model, must be determined. The processing units for computational convenience, like hyperbolic tangent sigmoid functions are easily differentiable, and are employed in the present model:

$$h_i = \frac{2}{(1+\exp(-2n))-1} \tag{1}$$

Also, in feed forward ANN the architecture only consists of forward connections. This is illustrated in Fig. 1.

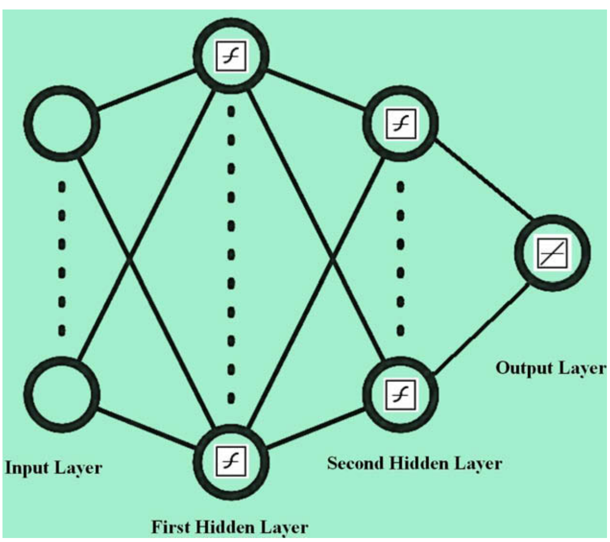

Fig. 1. Schematic architecture of neural network.

Table 1
Input parameter information.

No.	Inputs	Min	Max	Mean	SD
1	Final thickness (mm)	1.5	16	5.244903	3.155532
2	Final weight (kg)	5097	28030	18502.91	3214.769
3	Initial weight (kg)	5202	28660	18874.26	3264.811
4	Initial width (mm)	650	1850	1277.022	205.7713
5	Furnace temp. (°C)	1164	1296	1229.77	23.4407
6	Roughing temp. (°C)	932	1122	1058.281	14.00645
7	Finishing temp. (°C)	782	960	881.1131	23.32006
8	Coiling temp. (°C)	517	729	610.5108	18.02052
9	C (wt%)	0.03	0.21	0.126968	0.02545
10	Si (wt%)	0	0.347	0.070235	0.084277
11	Mn (wt%)	0.175	1.38	0.658662	0.206133
12	P (wt%)	0.001	0.026	0.006786	0.002377
13	S (wt%)	0	0.02	0.008637	0.002686
14	Cu (wt%)	0	0.264	0.029318	0.011597
15	Al (wt%)	0.007	0.093	0.045926	0.010957
16	N (ppm)	15	90	39.784	9.221
17	Nb (wt%)	0	0.06	0.004854	0.009032
18	V (wt%)	0	0.043	0.003378	0.001607
19	Ti (wt%)	0	0.042	0.001654	0.002318
20	Mo (wt%)	0	0.022	0.003654	0.004104
21	Cr (wt%)	0.001	0.194	0.011992	0.008007
22	Ni (wt%)	0.016	0.243	0.028205	0.004679
23	C_{eq} (wt%)	0.068032	0.437799	0.2443845	0.0534388

SD: standard deviation, C_{eq}: carbon equivalent.

2.2. Experimental database

The neural network method is an empirical method. For this reason, the results are strongly dependent to the given data. In this work, the annual product data reports of Mobarakeh Steel Company (MSC) for hot strip mills, were used. The input parameters included:

(i) Final thickness.
(ii) Initial and final weight.
(iii) Initial width.
(iv) Reheating, roughing, finishing and coiling temperatures.
(v) The chemical composition (14 elements).
(vi) The carbon equivalent.

A total number of 70,234 examples were available for modeling the network. Since the number of available data is too many, the

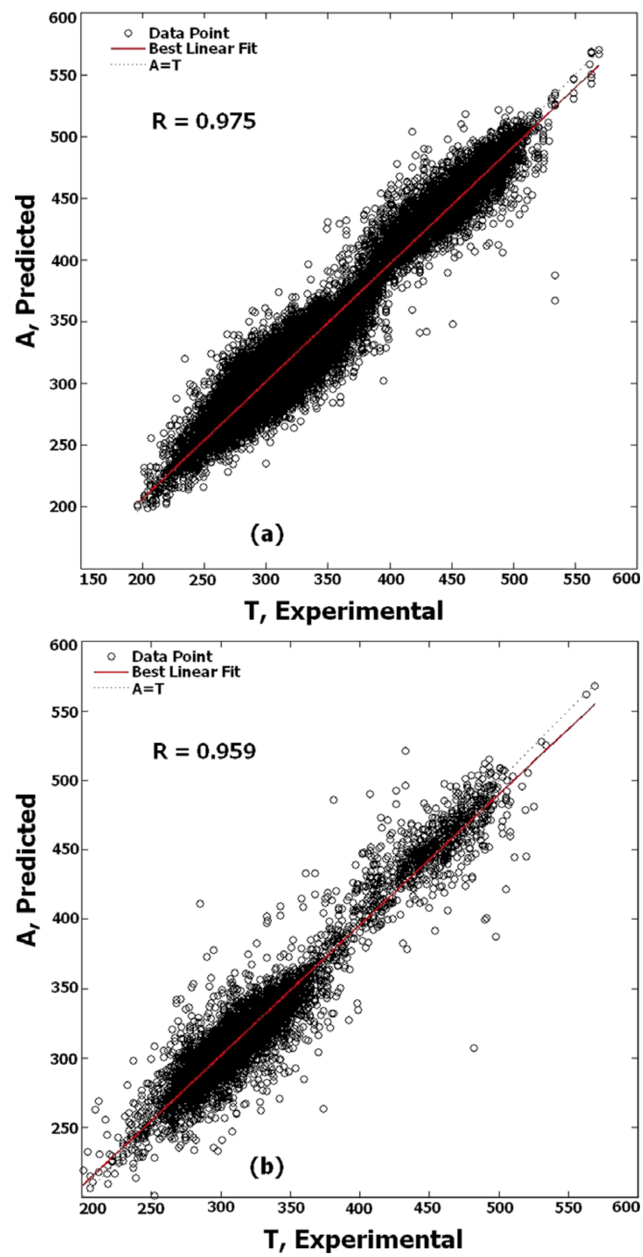

Fig. 2. Behavior of model on (a) training data, and (b) test data.