Advances in Engineering Software 45 (2012) 91–99

Contents lists available at SciVerse ScienceDirect

Advances in Engineering Software

journal homepage: www.elsevier.com/locate/advengsoft

Artificial neural network predictors for mechanical properties of cold rolling products

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ARTICLE INFO

Article history:
Received 12 March 2010
Received in revised form 8 June 2011
Accepted 31 August 2011
Available online 1 November 2011

Keywords:
Computer simulations
Mechanical property
Artificial neural network
Steel
Cold rolling
Estimation

ABSTRACT

Controlling product mechanical properties is an important stage in steel production lines. Conventionally, direct tensile tests are employed for this purpose; but their disadvantage is their high cost. The main objective of this paper is to develop an intelligent indirect method based on Artificial Neural Networks (ANN) for monitoring product mechanical properties without the need for expensive laboratory tests. The inputs into the proposed intelligent system include a wide variety of parameters from all production stages which it uses to predict such properties as Yield Strength (YS), Ultimate Tensile Strength (UTS), and Elongation (EL) as output. Moreover sensitivity analysis is performed based on using ANNs trained by data from three different grades because changing domains of input parameters is wider in these sets of data. Results show that the reduction in skin pass, the thickness after tandem and the ratio of Nitrogen to Aluminum are the effective parameters for all three mechanical properties among other inputs. Also, the thickness reduction in tandem affects the YS and EL values significantly, but UTS is not sensitive to this parameter noticeably. The variation of Vanadium content changes UTS value considerably.

1. Introduction

Maintaining product consistency along with high quality in metallurgical plants has become a widespread concern as a result of increasing global competition. As is the case with other industries, the objectives are always higher productivity and better quality of the final product. Enhanced product quality requires identification of the effects of each process parameter on product properties. This puts pressure on steel manufacturers to develop better and more accurate models of processes in order to optimize production conditions for better quality. Steel consumers such as the automotive industry in particular, constantly demand for higher quality steel [1]. They demand higher strengths but with less material to be used. This means reduced material weight and fuel consumption with increasing safety and crash-worthiness of vehicles.

Known as a complex system with a high level of non-linearity and an unknown and time-varying nature, the metal rolling process is difficult to represent in mathematical models [2]. Clearly, estimation of steel properties based on models of the chemical and physical processes during melting is complicated too as it needs a deep metallurgical understanding of each individual step and requires tedious recalculations or even experimental tests that are both expensive and time-consuming. Nowadays, Artificial Neural Network (ANN) modeling offers a powerful alternative. An ANN learns from examples and generalizes without any prior knowledge about their nature and interrelationships [3]. It dramatically helps in industrial situations where scientific background knowledge of the problems involved is often lacking [4]. Neural networks have been the focus of great attention due to their capacity in solving non-linear problems [5].

In 2001, Perzyk and Kochanski [6] predicted ductile cast iron quality by ANN using the chemical composition of the melt only. Guo and Sha [4] estimated the properties of Maraging steel using ANN. They used alloy composition, processing parameters and working temperature as input parameters. Ozerdem and Kolukisa [7] predicted mechanical properties of AISI10XX series carbon steel bars using only three chemical contents as inputs. Capdevila et al. [1] analyzed the influence of processing on strength and ductility of automotive low carbon sheet steels, but they did not investigate the effects of Coiling Temperature (CT) because of lack of a database.

Comparison with the indicated references showed that the authors of Ref. [8] used indeed 16 input parameters. Thirteen of them representing the crystallographic texture, one for the carbon content, one for the carbide size and one for the rolling degree.

Reddy et al. [9] modeled medium carbon steels with alloy compositions and heat treatment parameters as input, but they did not use cold rolling parameters in their model.

In the present work, an intelligent model based on some artificial neural networks is proposed for predicting the mechanical

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doi:10.1016/j.advengsoft.2011.09.016

properties of ST14 steel which is identical to SPCE in the JIS standard or to CRSP1 in the British Standard. Moreover we have used data from three grades including ST12, ST13, and ST14 for training new ANNs. Changing domain is wider in these sets of data. So, sensitivity analysis is performed based on using ANNs trained by these data.

In previous studies, input parameters would first be selected to be used for designing the model. In this work, however, ANNs with different input parameters are trained and compared, which allows the effect of each input to be investigated on the model's performance. Three ANNs based on a multilayer feed forward topology and a back propagation algorithm are proposed to estimate the outputs.

The Levenberg–Marquardt method is employed to enhance the performance of the calculations [10]. A wide variety of standard statistical parameters is then used to ensure satisfactory agreement between predicted and observed data. The proposed neural network approach reduces the number and the cost of experimental tests commonly required to determine the mechanical properties of ST14 steel. In addition, the ANN predictors may also adjust the values of input parameters to achieve desired steel characteristics.

2. Intelligent process model based on neural networks

Artificial neural network is a mathematical model that can learn and generalize the things learned. It makes a mapping function from input to output, giving information about practical phenomena. Because of the non-linear properties of neural networks, they are suitable for describing complex non-linear phenomena which linear modeling techniques fail to describe. Basically, all the processes that have an adequate number of measured data can be modeled by ANN [11].

Each ANN is made up of some neuron sets. A neuron adds up the weighted input, associated it with a bias, and passes the results on through a non-linear transfer function. An ANN has an input layer, one (or more) hidden layer(s), and one output layer. Each node in the input layer represents one input variable. Information from the input layer becomes processed in the neurons of the hidden layer(s). Finally, the output vector is computed in the output layer. It has been shown that a three-layer network with sigmoid-type transfer functions in the hidden layer can approximate any practical function if given enough neurons in the hidden layer [3]. A schematic view of a multi-layer Artificial Neural Network (ANN) is shown in Fig. 1.

The most popular approach to ANN learning is the feed forward method which normally includes the following steps:

1. Collection of data and determination of input/output variables.
2. Pre-processing of the data and dividing them into training and testing data sets.
3. Training the network with the associated data whereby the target output at each output neuron is compared with the actual network output whereby the difference or error is minimized by adjusting the weights and biases through some training algorithms [3].

Finally, the trained network is tested and verified using test data not included in the training data.

2.1. Training algorithm

Since this application requires training of sets of observed data in a supervised manner, a feed forward network topology is suitable to use [12]. Feed forward has become the standard for some

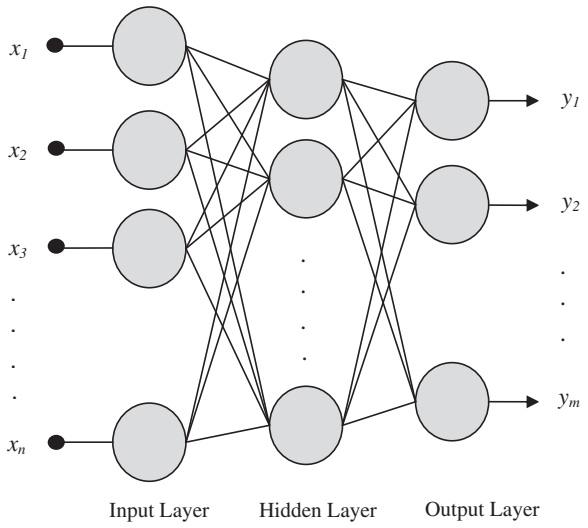

Fig. 1. Schematic of a multi-layer Artificial Neural Network (ANN).

years for training ANNs by a method called Back Propagation (BP) in industrial applications. The objective of the BP algorithm is to minimize a predetermined error function given by:

$$E = \sum_{Q} \sum_{P} (y_i - t_i)^2 \tag{1}$$

where y_i is a component of ANN output vector, t_i is the component of the target output vector, P is the number of output neurons, and Q is the number of training patterns.

The BP algorithm uses a chain rule to compute the derivatives of the error function with respect to the weights and biases in the hidden layers. It is called back propagation because the derivatives are computed first at the last layer of the network and then propagated backward through the network using the chain rule to compute the derivatives in the hidden layers [3]. In order to minimize the error function, different optimization methods such as Conjugate Gradient (CG) and Levenberg–Marquardt (LM) have been used. Generally, for a neural network which contains up to a few hundred weights, the LM algorithm has the fastest convergence [10]. Thus, in this research, the LM method is used to optimize weights and biases of the networks toward error function minimization.The LM algorithm is a modified version of the Newton's method which was designed to minimize functions in the form of a sum of squares like Eq. (1), without having to compute the Hessian matrix,$\nabla^2 E$. The Hessian matrix is the second derivatives of the performance index at the current values of the weights and biases. So, it can be approximated as

$$\nabla^2 E = 2J^T J \tag{2}$$

where J is the Jacobean matrix and contains the first derivatives of the networks error with respect to the weights and biases.

By applying the approximation of the Hessian matrix into the Newton's method, we obtain the LM algorithm given by

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T V(x_k) \tag{3}$$

where $V(x_k)$ is the error vector. The advantage of this method is that the Jacobean matrix (J) is computed through a standard BP technique [3], which is much less complex than computing the Hessian matrix.

2.2. Training and testing of the ANNs

There are many parameters to be determined such as number of hidden layers, number of neurons in each layer, and initial values

of the interconnection weights which affect the reliability and trust worthiness of neural network results. To find the best structure of the hidden layer, a numerical optimization approach based on global search in the whole available space is employed. In this research, the available space is defined to include all neural networks which have 1 or 2 hidden layers with 3–15 neurons in each. Particularly, this search space is wide enough to find approximately the best ANN for this application.

When the number of ANN outputs is increased, the output errors usually increase because of the effects of each output on the other outputs in the BP algorithm. Also, in the training state, the training time increases dramatically. Thus, in this paper, a separate ANN containing only one output is developed and trained for each of the desired mechanical properties including YS, UTS, and EL as shown in Fig. 2.

The initial values of the interconnection weights are chosen randomly about four times for each ANN in its training step. Network transfer functions are selected between the hyperbolic tangent sigmoid and the log sigmoid.

In the pre-processing step, it is often useful to scale the inputs and targets so that they always fall within a specific range. This is because most statistical learning techniques, including ANN modeling, improve model performance by normalizing the training data [13]. The relation used for the normalization is:

$$x_N = (d_{\max} - d_{\min}) \frac{x - x_{\min}}{x_{\max} - x_{\min}} + d_{\min} \tag{4}$$

where x_N is the normalized value of the variable x whose maximum and minimum values are given by $x_{\max}$ and $x_{\min}$, respectively. x_N

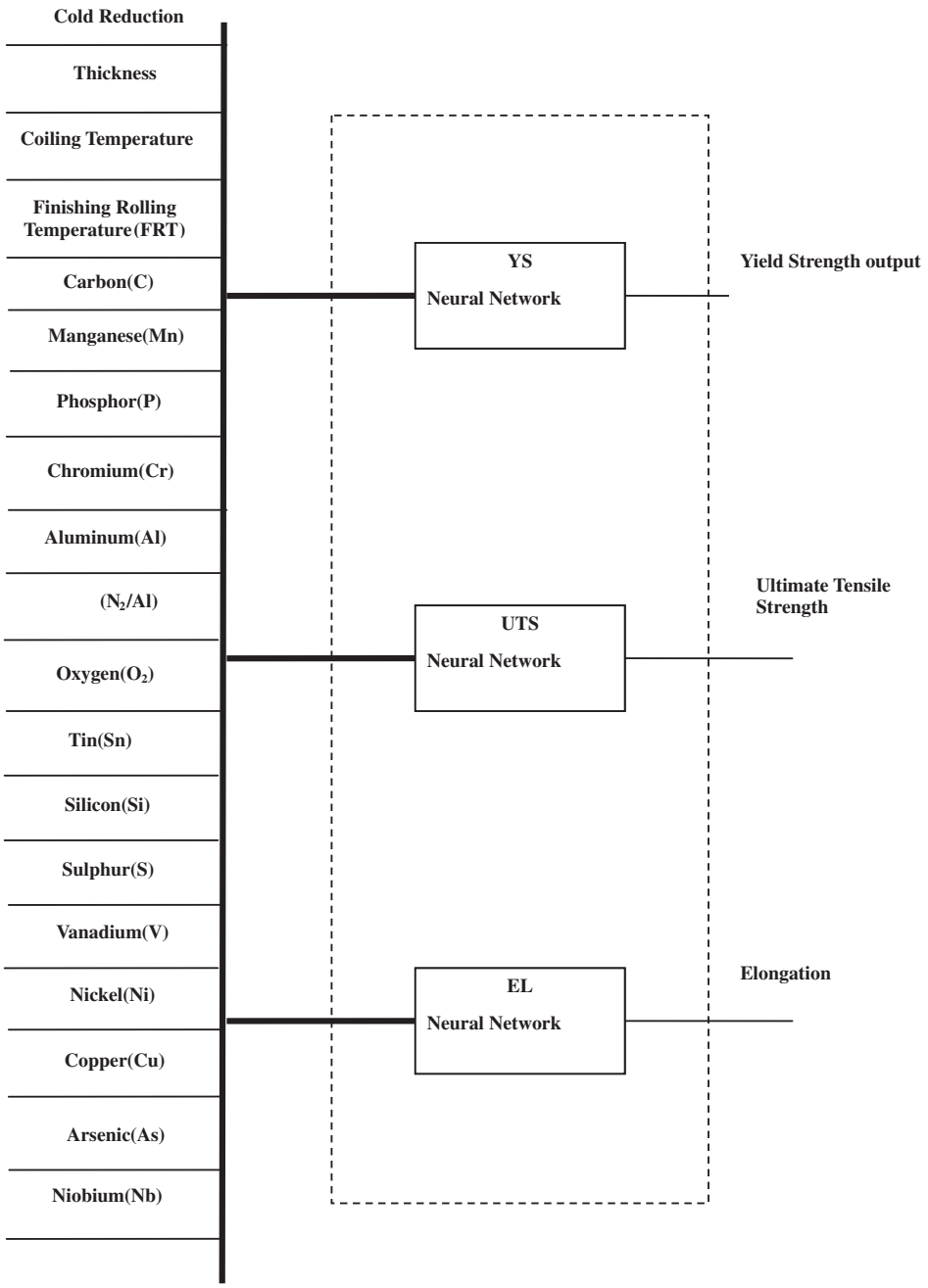

Fig. 2. Inputs, outputs, and the structure of the proposed ANN models.

Table 1
Input parameters to the neural networks.

Chemical composition	Hot rolling variable	Cold rolling variable
Carbon (C), Manganese (Mn), Phosphor (P), Copper (Cu), Chromium (Cr), Aluminum (Al), Tin (Sn), Nitrogen (N_2), Oxygen (O_2), Sulfur (S), Silicon (Si), Nickel (Ni), Arsenic (As), Vanadium (V), Niobium (Nb), Molybdenum (Mo), Titanium (Ti), Boron (B), Hydrogen (H_2)	Finishing Rolling Temperature (FRT) Coiling Temperature (CT)	Changing ratio of thickness in tandem Thickness before tandem Position of coil in box annealing Coil Retention Time in box annealing

Table 2
Statistical indexes of input and output data in the training process.

	Training data				
	Mean	STD	Min	Max	
Inputs	Reduction (%)	0.319	0.058	0.240	0.566
	Thickness (mm)	3.2535	0.8292	2.000	5.3000
	CT (°C)	625.064	19.821	543.85	795.600
	FRT (°C)	886.602	13.576	830.940	919.390
	Al (wt.%)	0.0474	0.0577	0.025	0.070
	N_2 (ppm)	86.7	25.2	0.0	200
	C (wt.%)	0.0493	0.0189	0.033	0.0156
	Mn (wt.%)	0.2309	0.0946	0.174	1.083
	P (wt.%)	0.0063	0.0021	0.002	0.019
	Cr (wt.%)	0.0084	0.0021	0.004	0.017
	O_2 (ppm)	15.897	20.007	0	65
	Sn (wt.%)	0.0059	0.0024	0	0.012
	Si (wt.%)	0.0121	0.0198	0.001	0.201
	S (wt.%)	.0099	0.0027	0.003	0.018
	V (wt.%)	0.0021	0.00083	0.001	0.006
	Ni (wt.%)	0.0301	0.0028	0.023	0.036
	Cu (wt.%)	0.0314	.0095	0.007	0.058
	As (wt.%)	0.00094	0.00085	0.0	0.003
	Nb (wt.%)	0.0018	0.0012	0.0	0.005
Outputs	YS (MPa)	179.182	24.508	136	350
	UTS (MPa)	305.946	17.479	274	414
	EL (%)	40	3.100	27	48

Table 3
Statistical indexes of input and output data in the testing process.

	Testing data				
	Mean	STD	Min	Max	
Inputs	Reduction	0.318	0.056	0.240	0.566
	Thickness	3.2416	0.8256	2.000	5.3000
	CT (°C)	626.889	24.030	587.470	804.710
	FRT (°C)	886.360	15.594	831.020	917.900
	Al (wt.%)	0.0478	0.0055	0.033	0.059
	N_2 (ppm)	84.6	25.9	0.0	175.7
	C (wt.%)	0.0491	0.0172	0.033	0.141
	Mn (wt.%)	0.2242	0.0699	0.177	0.755
	P (wt.%)	0.0061	0.00198	.003	0.019
	Cr (wt.%)	0.0084	0.0019	.005	0.014
	O_2 (ppm)	14.911	19.005	0	65
	Sn (wt.%)	0.0058	0.00251	0	0.012
	Si (wt.%)	0.00999	0.0112	0.003	0.16
	S (wt.%)	0.0101	0.0028	0.003	0.017
	V (wt.%)	0.0021	0.00074	0.001	0.005
	Ni (wt.%)	0.02997	0.0028	0.021	0.038
	Cu (wt.%)	0.0308	0.0104	0.007	0.058
	As (wt.%)	0.000901	0.000864	0.0	0.003
	Nb (wt.%)	0.001757	0.001095	0.0	0.005
Outputs	YS (MPa)	175.688	18.910	140	258
	UTS (MPa)	305.381	13.674	276	400
	EL (%)	40.114	2.800	29	47

will be in the range of $[d_{min}, d_{max}]$. In this case, inputs and targets are scaled to put in the range of $[d_{min} = -1, d_{max} = +1]$.

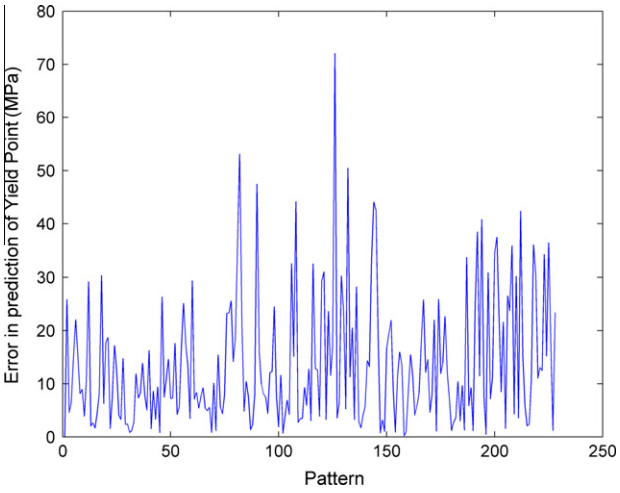

Fig. 3. Error in the prediction of Yield Strength (YS).

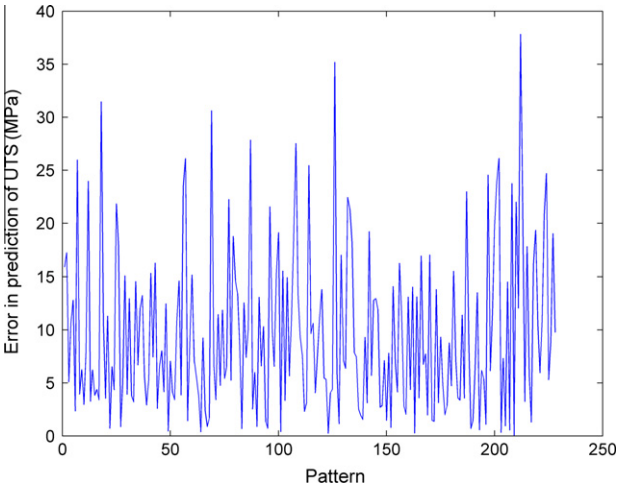

Fig. 4. Error in the prediction of Ultimate Tensile Strength (UTS).

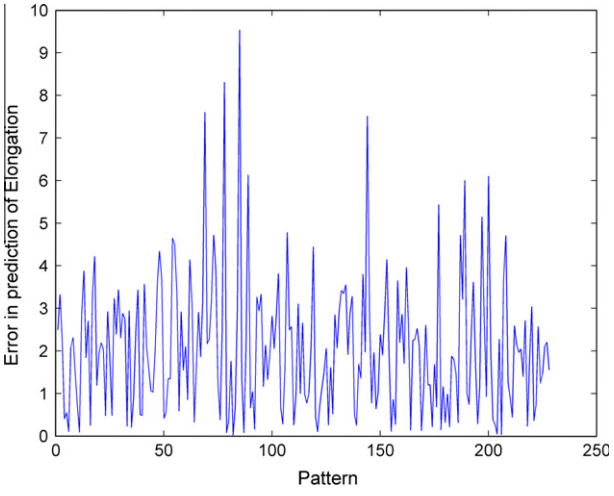

Fig. 5. Error in the prediction of Elongation (EL).

Table 4
Statistical measures of the mechanical properties predicted by the ANN models and observed values.

	Yield Strength (YS)			Ultimate Tensile Strength (UTS)			Elongation (EL)		
Scenario	Mean	SD	MAPE	Mean	SD	MAPE	Mean	SD	MAPE
Observed	178.24	22.34	0.00	307.06	16.99	0.0	39.93	2.99	0.00
ANN prediction	170.32	17.66	7.22	304.84	15.77	3.07	39.86	3.01	5.14

To validate the trained ANNs in each step, testing data sets not used in the training state were put into the neural networks to obtain the outputs of the ANNs.

3. Experimental database

Construction of a data set is the first essential step to develop an ANN model. In this study, two different data sets were used. First one includes 916 input–output data sets of ST14 steel in which each one have 25 input parameters including chemical compositions as well as hot and cold roll process variables as shown in Table 1. Second data set includes 6797 input–output data sets of three steel grades including ST12, ST13, and ST14. These data sets have all input parameters of the first data set except four chemical compositions including Ni, Cu, As and Nb. However, the interval changes of these parameters are small. So they have minor effect on the mechanical properties in the current case and the extent of accuracies is adequate for sensitivity analysis.

The output data comprised three important mechanical properties including Yield Strength (YS), Ultimate Tensile Strength (UTS), and Elongation (EL).

Both property-related and network input parameters were selected on the basis of physical background and previous experience of how a certain target property could be determined. It was emphasized in the literature that the chemical compositions as well as hot and cold roll process variables affect on all three parameters UTS, YS and Elongation [14–18].

Other parameters with no obvious effects on the improvement of the ANN model were excluded in order to increase the efficiency and speed of calculations and to simplify the model for further applications [4].

ST14 is a specific grade of steel. Thus, variations in some important production parameters are too small to change the ANN outputs. Actually, when the ANN model is trained, these parameters come into the ANN model as constant biases to adjust the final model. However, the effects of this set of parameters are considered in the modeling, they do not need to appear as ANN inputs directly. Therefore, the number of inputs to the ANN model is reduced while faster and online modeling becomes possible. In the annealing unit, for example, the coil retention time in box annealing as well as the temperature of the annealing process are almost fixed for all ST14 products. This is also true with certain chemical variables such as weight of Molybdenum (Mo) which is almost constant for the special grade of steel. Based on these considerations, the six parameters including Molybdenum (Mo), Hydrogen (H_2), Boron (B), Titanium (Ti), coil position in the box annealing, and coil's retention time in box annealing did not directly appear in the set of ANN inputs.

Finally, 19 input data including cold reduction, thickness, Coiling Temperature, Finishing Rolling Temperature (FRT), contents of Carbon (C), Manganese (Mn), Phosphorus (P), Chromium (Cr), Aluminum (Al), Oxygen (O_2), Tin (Sn), Silicon (Si), Sulfur (S), Vanadium (V), Nickel (Ni), Copper (Cu), Arsenic (As), Niobium (Nb) and ratio of Nitrogen to Aluminum (N_2/Al), were selected for the ST14

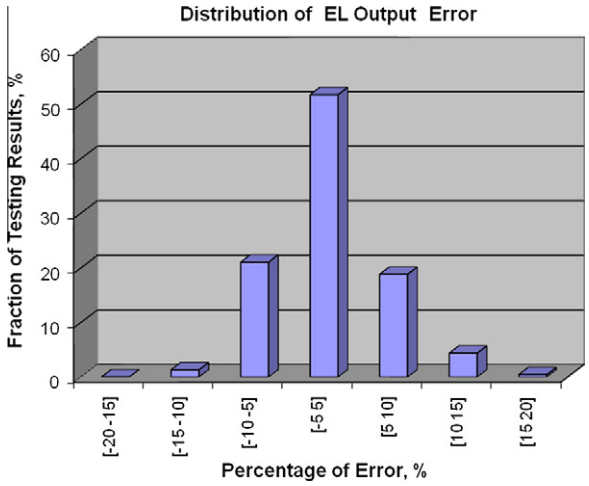

Fig. 7. The distribution of predicted values for EL vs. MAPE.

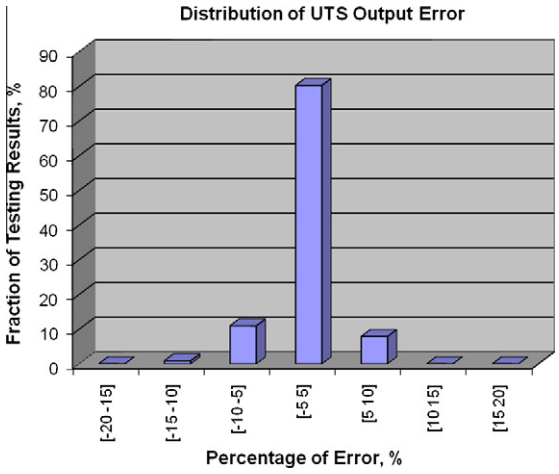

Fig. 6. The distribution of predicted values for UTS vs. MAPE.

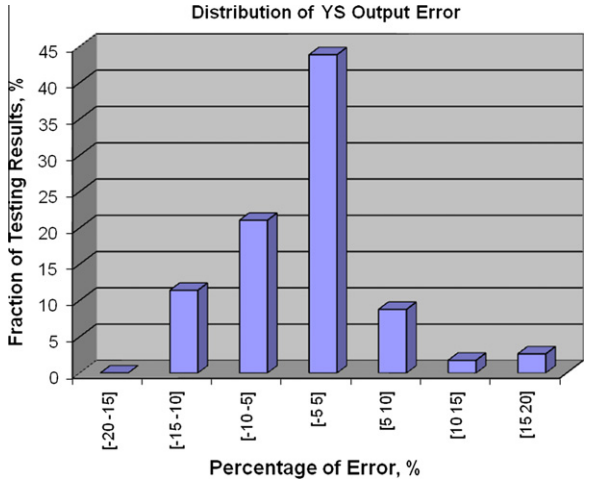

Fig. 8. The distribution of predicted values for YS vs. MAPE.

case. The selected inputs considerably influence the outputs of the ANNs which illustrate the mechanical properties including Yield Strength (YS), Ultimate Tensile Strength (UTS), and Elongation (EL). The inputs, outputs, and the structure of the proposed ANN models are shown in Fig. 2.

4. Experimental results

4.1. Using ST14 data for ANN modeling

A randomly selected 688 data sets (approximately 75%) were used to train the neural networks and the remaining 228 data sets (approximately 25%) were employed to test and verify the networks. The statistical indexes such as mean, standard deviation, maximum, and minimum of the input and outputs of training and testing data in this study are shown in Tables 2 and 3, respectively.

As mentioned, by eliminating the inputs which had almost identical values in most data sets, the ANN models were trained with 19 inputs, different numbers of hidden layers and different numbers of neurons in each layer. Finally, after training and testing more than 3400 networks, the optimized ANN models for YS, UTS and EL were developed and the values for these parameters were obtained in the global space. The best model for YS was found to be an 8-4-1 structure comprising 2 hidden layers with 8 and 4 neu-

Table 5
Characteristics of data used for sensitivity analysis in each stage and their effect on the interval changes of mechanical properties predicted by the ANN model.

	Min	Max	Mean (reference)	YS variation (MPa)	UTS variation (MPa)	EL variation (%)
FRT (°C)	855	885	870	2.5	1.6	0.29
CT (°C)	560	590	575	2	5	0.34
Reduction in tandem	2.5	4.17	3.33	13	3	0.73
Thickness (mm)	0.5	1.5	1	23	25	1.84
Skin elongation	0.6	1.1	0.85	25	25	2.97
C (wt.%)	0.035	0.055	0.045	1.2	5	0.37
Si (wt.%)	0.005	0.0015	0.001	8	7	0.25
Mn (wt.%)	0.19	0.23	0.21	2	5	0.33
N/Al	0.5	1.3	0.8	10	8	1.18
N (ppm)	25	50	37.5	2	4.5	0.42
O_2 (ppm)	25	50	36	2	2.8	0.2
V (wt.%)	0.001	0.0035	0.0023	2	14	0.64
S (wt.%)	0.05	0.01	0.075	2.9	7	0.21
P (wt.%)	0.005	0.011	0.008	3.9	6	0.1
Cr (wt.%)	0.007	0.010	0.0085	2.3	4.5	0.04

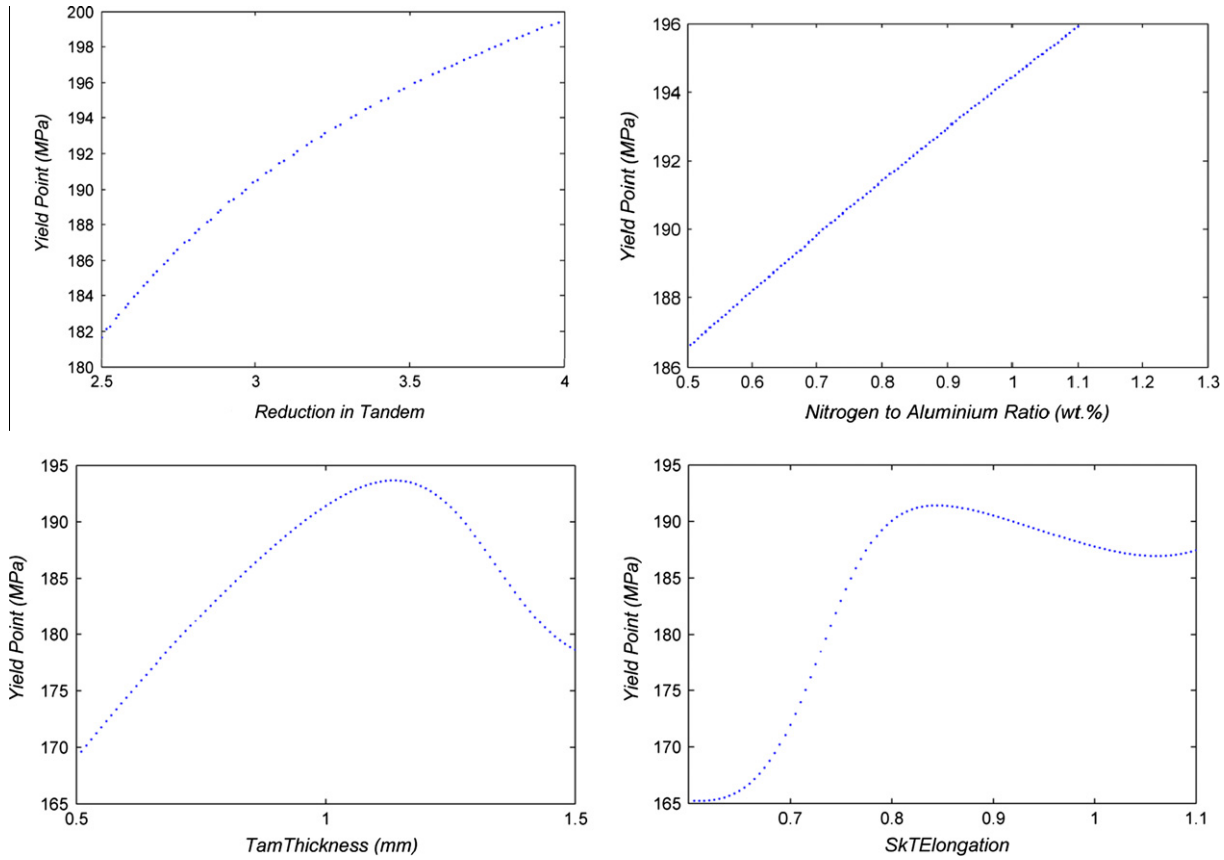

Fig. 9. Sensitivity of YS relative to effective parameters.

rons in the first and second hidden layer and one output, with a hyperbolic tangent sigmoid transfer function. The optimum solution for UTS was found to be a network with a 3-7-1 structure and a hyperbolic tangent sigmoid transfer function. Finally, the best for EL was a network with a 4-5-1 structure and logarithm sigmoid transfer functions.

Test data sets were put into the ANN models developed to obtain the predicted outputs. Figs. 3–5 present the measured values and those predicted by the ANN models.

For the test sets, the deviations of the predicted outputs from the measured experimental data were determined, using standard statistical analyses, to evaluate the accuracy of the proposed ANN models in predicting the desired product mechanical properties. The statistical measures used included mean values, standard deviations (SD), and mean absolute percentage error (MAPE) of the output data and output errors, as reported in Table 4. MAPE is the computed average of absolute percentage errors. Formula for calculation this parameter is [19]:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - t_i}{t_i}\right| \times 100 \quad (5)$$

where t_i is the actual value of the quantity being forecast, and y_i is the forecast and N is number of predicted values.

As seen here, a good agreement is observed between the predicted and observed values. For example, in the worst case, the mean of errors for predictions were 7.22%, 5.14%, and 3.07% for YS, EL, and UTS, respectively.

The distributions of the predicted values for UTS, EL, and YS vs. the different error intervals are shown in Figs. 6–8. It can be seen that the proposed intelligent ANN models successfully predicted ST14 steel's UTS, EL, and YS in 99.1%, 91.7% and 73.7% of the testing data sets, respectively, with an accuracy level of more than 10%. This is evidence of the capability of the proposed model to make accurate predictions under real-life industrial conditions, which leads to considerable savings in cost and time.

4.2. Sensitivity analysis

In this section, numerical experiments have been performed to investigate the effects of different input parameters on the mechanical properties. sensitivity of outputs is analyzed based on artificial neural networks which are trained by using the input data from three grades of steel. Using data from various grades of steel provides a wide range of variation in each input parameter. For sensitivity analysis, in each stage only one input parameter changes between its minimum and maximum of duration and other ones fixed in their reference condition. Table 5 shows data related to the minimum, maximum and means of experimental input parameters. Means of experimental input parameters is chosen as reference condition. Moreover interval changes of mechanical properties are given in Table 5. In this table, it can be seen that:

– The thickness and the reduction in skin pass are the most effective parameters for all three mechanical properties among other

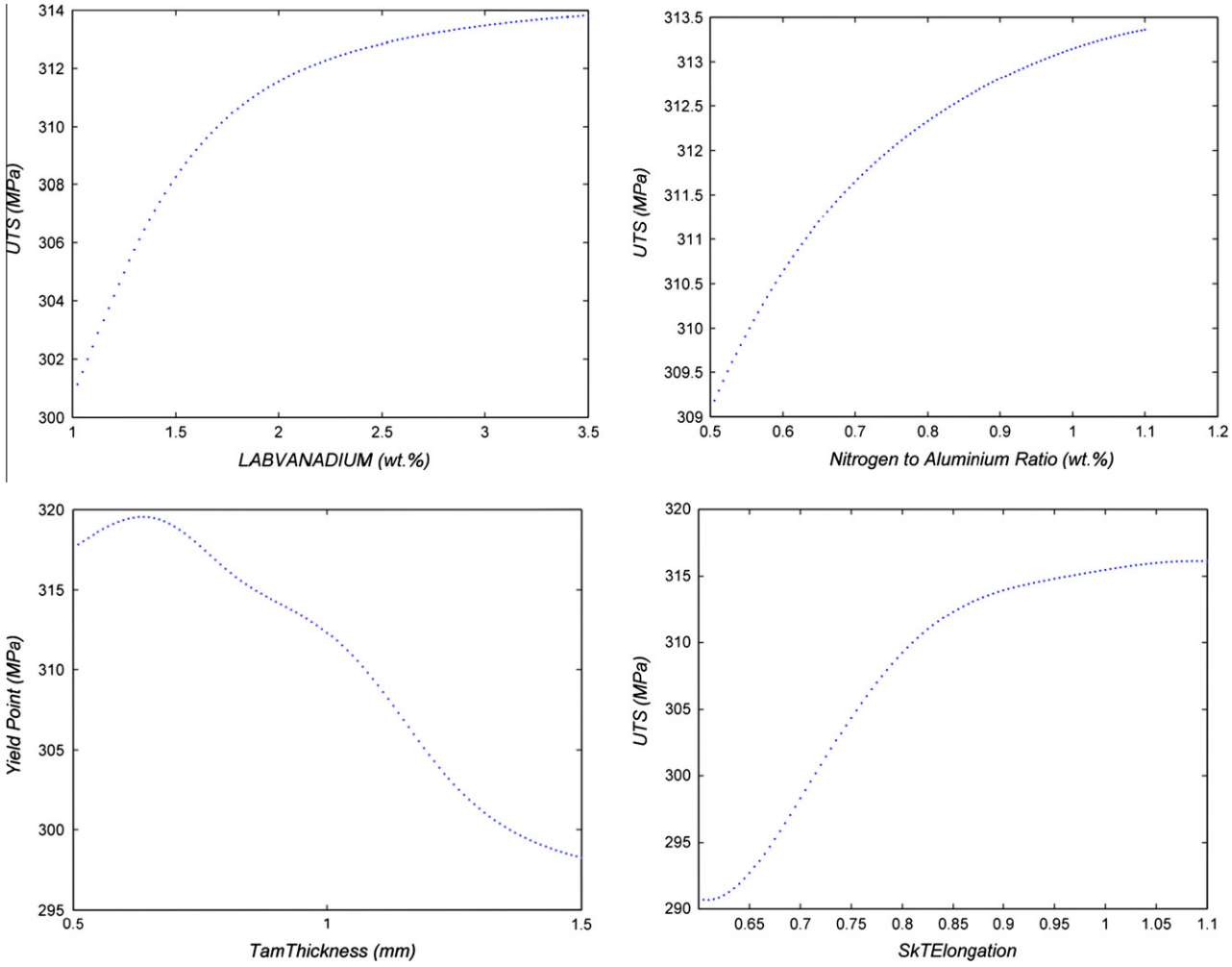

Fig. 10. Sensitivity of UTS relative to effective parameters.

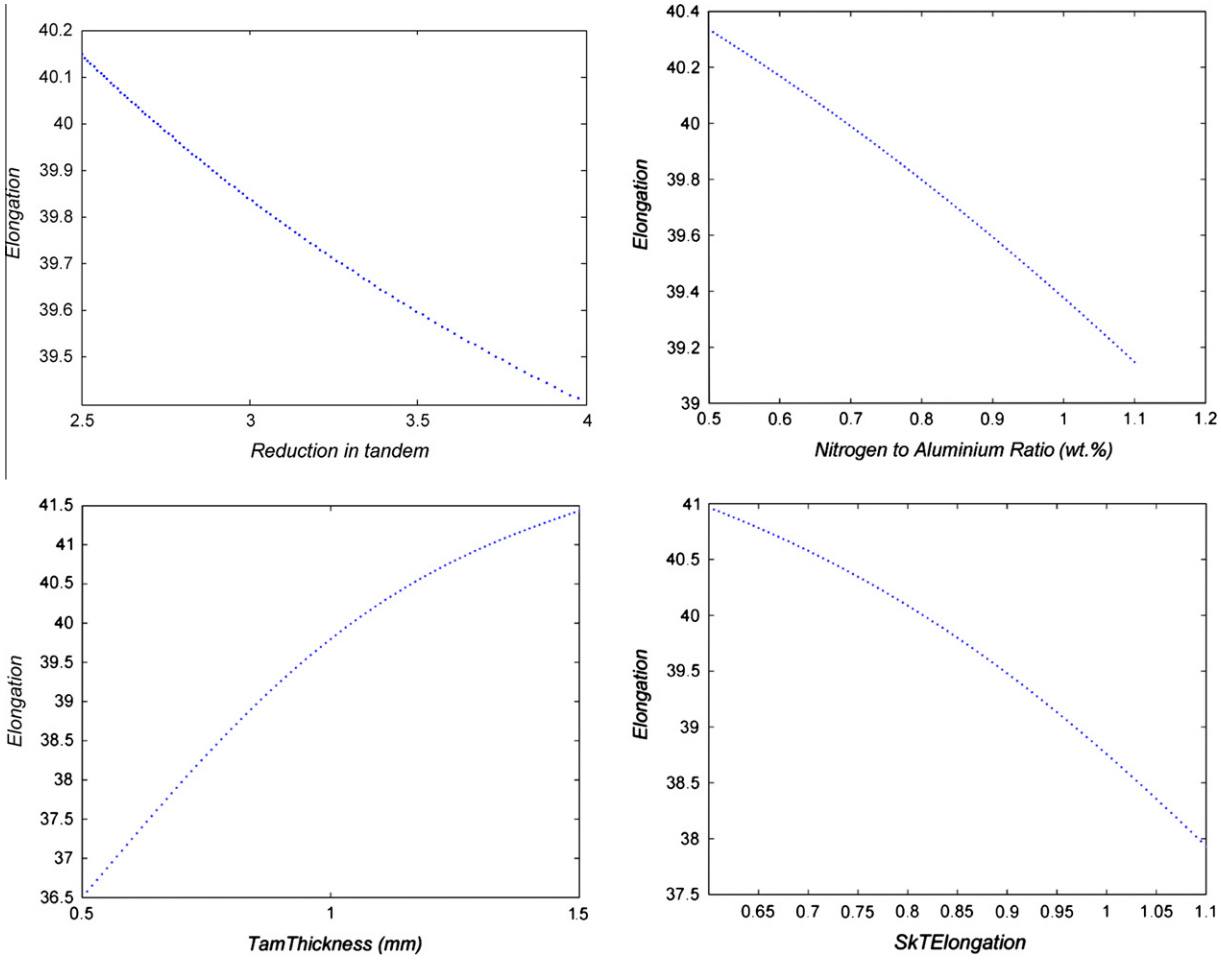

Fig. 11. Sensitivity of EL relative to effective parameters.

inputs of system. These results are reasonable because skin pass is the last influencing step on the mechanical properties in steel making. So special consideration should be applied in this step in order to improve mechanical properties.

- The thickness reduction in tandem affects the YS and EL values significantly but UTS is not sensitive to this parameter noticeably.
- The ratio of Nitrogen to Aluminum is important for YS, UTS and EL. This observation have been confirmed in the literature [16].
- Variation of Vanadium content changes UTS value considerably.

Figs. 9–11, respectively, show the variation of YS, UTS, and EL relative to more effective input parameters. In these figures, Tam thickness is thickness after tandem mill. It can be seen that the YS increase but the EL decrease with increasing the reduction in tandem mill. This is in good agreement respect to the results of other studies in this area [20].

5. Conclusion

In this paper, Artificial Neural Network (ANN) models were used to predict the mechanical properties of ST14 steel produced in Mobarakeh Steel Company in an attempt to save product quality control costs and time. Networks with nineteen inputs including cold reduction, thickness, contents of Cr, Ni, V, Cu, As, Nb, C, Mn, P, Si, S, Al, N_2, O_2, and Sn, Coiling Temperature and Finishing Rolling Temperature (FRT), were trained for the intelligent prediction of such mechanical properties as Yield Strength (YS), Ultimate Tensile Strength (UTS), and Elongation (EL). All essential parameters in ANN models were evaluated in the training state to select the best ANN models within a wide search space containing all the available and possible solutions. Standard statistical measures were employed to evaluate the performance of the proposed ANN models in using the testing data set in the ANNs. The testing results revealed the capability of the ANN models developed to predict the mechanical properties of untrained data with a satisfactory accuracy. Moreover, sensitivity analysis is performed based on using ANNs trained by data from three grades. Results show that the reduction in skin pass, the thickness after tandem and the ratio of Nitrogen to Aluminum are the effective parameters for all three mechanical properties between other inputs. The ratio of Nitrogen to Aluminum is less important than other two parameters. Also, the thickness reduction in the tandem affects YS and EL values significantly but UTS is not sensitive to this parameter.

Acknowledgments

The authors would like to acknowledge Mobarakeh Steel Company for funding this research work and for supplying the experimental data. Especially, Dr. Izadi and Mr. Rasouli from the R&D Department deserve our special thanks. Mr. Nazeri from the Cold Rolling Technical Office, MSc, also provided invaluable support, without whose assistances this work would not have become possible.

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