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Research paper

Estimation of Austenitizing and Multiple Tempering Temperatures from the Mechanical Properties of AISI 410 using Artificial Neural Network

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Abstract

This research involved a study of the heat treatment conditions effect on the mechanical properties of martensitic stainless steel type AISI 410. Heat treatment process was hardening of the metal by quenching at different temperature 900°C, 950°C, 1000°C, 1050°C and 1100°C, followed by double tempering at 200°C, 250°C, 300°C, 350°C, 400°C, 450°C, 500°C, 550°C, 600°C, 650°C and 700°C, were evaluated and study of some mechanical properties such as hardness, impact energy and properties of tensile test such as yield and tensile strength is carried out. Multiple outputs Artificial Neural Network model was built with a Matlab package to predict the quenching and tempering temperatures. Also, linear and nonlinear regression analyses (using Data fit package) were used to estimate the mathematical relationship between quenching and tempering temperatures with hardness, impact energy, yield, and tensile strength. A comparison between experimental, regression analysis and ANN model show that the multiple outputs ANN model is more accurate and closer to the experimental results than the regression analysis results.

Keywords: *Artificial neural network ANN, austenitizing temperature, multiple tempering, regression analyses.*

1. Introduction

Stainless steels are iron base alloys containing at least 10.5 % Cr. Few stainless steels contain more than 30 % Cr or less than 50 % Fe. Other elements added to improve particular characteristics include molybdenum, titanium, nickel, aluminum, niobium, silicon, copper, sulfur, nitrogen, and selenium. Amounts of carbon is normally ranging less than 0.03 % to over 1.0 % in grades of certain martensitic [1].

Essentially alloys of Martensitic stainless steels are carbon and chromium that possesses in the hardened condition of a martensitic crystal structure and distorted body-centered cubic BCC. They are resistant to corrosion, hardenable by heat treatments and ferromagnetic [2].

Artificial neural networks represent different methodology to the implementing of mechanical properties. In the materials science, ANNs model has increased use due to better results achieve of prediction. After learning the relationship between input and output data, this method becomes able to generate output data for any new input value. The ANN is very suitable method for prediction properties of material in the case of unknown the relevant factors, as well as for solving complex phenomena [3][4].

An overview of the relevant available literature,

Dobrzański and Honysz, (2009) [5] presented after heat treatment of steels, application of the artificial neural networks for prediction of mechanical properties. The mechanical properties, such as strength, impact resistance or hardness are predicted on the basis of such input parameters, which are geometrical dimensions of elements, type of heat treatment and the chemical compositions. After heat treatment, the results of the given range of input parameters obtained show is very good ability of constructed artificial neural networks to predict and described the mechanical properties of steels.

Smoljan, et al. (2010) [6] established a method of computer simulation based on experimental results and by regression analysis for mechanical properties of quenched and tempered steel. Also, used theoretical analysis of relevant properties which have an influence on the hardness of quenched and tempered steel. The proposed method of computer simulation of mechanical properties of quenched and tempered steel is based on predicted steel hardness. It was found that the proposed method can be successfully predicted the mechanical properties of quenched and tempered steel.

Titus et al. (2017) [7] developed based machine learning models a single layer and multilayer artificial neural network back propagation feed forward algorithm to predict the mechanical properties of hydrogen charged metallic materials. Model of feed forward Multilayer back propagation was employed to predicts the tensile strength. And model of feed forward single layer back propagation feed forward was used to predict the percentage of elongation. Studied and developed models for their capability of tested and validated with unknown inputs data.

Efendi et al. (2018) [8] developed by heat treatment process the microstructure of the steels and mechanical properties. The experimental results of steels quenched at 1100°C showed after tempering of 600, 650 and 700°C that had highest values of both elongation and tensile strength and after tempering at 600°C the best combination of elongation and tensile strength. Whereas, as tempering temperature increased, the mechanical properties of the steels decreased.

The objectives of the present Investigation of identifying the heat treatment parameters including the austenitizing and tempering temperature required to select suitable mechanical properties such as tensile strength, hardness and Impact energy for optimal engineering application using experimental and regression analysis.

Design and construct an artificial neural network ANN model as a tool applied to simulate the relationship between heat treatment and mechanical properties to determine and predict the austenitizing and tempering temperature of AISI 410 martensitic stainless steel.

2. Experimental Work

2.1 Chemical Composition of AISI 410 Martensitic Stainless Steel

Chemical composition of the AISI 410 martensitic stainless steel conducted by "METEK" spectrographic analysis Instrument GmbH, Boschstrasse, kleve, Germany. The sample contains 12.08% chromium, with small additions of copper, nickel, vanadium, silicon, manganese and molybdenum. This procedure was mentioned in our previous work in the part I [9].

2.2 Micro structural Analysis

Fifty-five microstructure specimens are prepared as circular disks of 12 mm diameter and 10 mm thickness. Optical microscopy was utilized to examine as received materials microstructure. The specimens were grinded by emery paper then polished and etched with vilella's reagent (1g Picric acid + 5 ml HCl + 100 ml ethanol) according to the ASTM Standard (E 407 - 99) [9].

2.3 Heat Treatment of Martensitic Stainless Steel

Heat treatment process was hardening of the metal by Oil quenching at different temperature 900°C, 950°C, 1000°C, 1050°C and 1100°C, followed by double tempering by water at 200°C, 250°C, 300°C, 350°C, 400°C, 450°C, 500°C, 550°C, 600°C, 650°C and 700°C, were evaluated and study the heat treatment effect on the microstructure of the alloy [9].

2.4 The Mechanical Properties of Martensitic Stainless Steel

Fifty-five samples are prepared for the tensile, impact, and hardness test according to the ASTM Standard (A 370 - 03a or E 8M - 01), (E 23 – 02a), and (E 18 - 02), respectively. This procedure was mentioned in our previous work in the part II [10].

3. Artificial Neural Network Modelling

In this investigation, the artificial neural network model is employed to simulate and predicted the austenitizing and tempering temperatures resulted from the experimental work depending upon the tested mechanical properties. This model is coded using Matlab package which as M-file basic function of Matlab saved, whereas a program of Matlab function develops to call the model results of the correct basis and weights. In general, use developed by Matlab code a graphical user interface GUI in order to simplify this model.

The artificial neural network model which is used to predict the austenitizing and tempering temperatures implemented by back-propagation algorithm and several different neural network algorithms.

3.1 The Training and Testing Patterns Selection

Training and testing, two subsets of data are employed, to build of the ANN model. Important steps of building a neural network model is selection of training data. The training set of data is used to updating the network biases and for computing the gradient and find the relationship between the input and output parameters and weights to diminish the training error. The ability of the learning process was evaluating by testing data set. Table 1 shown the total numbers of experimental values is 55 test cases are employed to train the neural network as training data and the parameters of the testing set contains approximately 20 % of total data. The testing set comprises of 11 cases and the training set contains 44 cases.

Table 1: Parameters of input and output

Item	Parameters	Range of Parameters		Units
		From	*To*	
Input Parameters	Rockwell Hardness	31.733	51.7	HRC
	Impact Energy	20	108	J
	Yield Strength	450	700	MPa
	Tensile Strength	821.488	1717.787	MPa
Output Parameter	Austenitizing Temperature	900	1100	°C
	Tempering Temperature	200	700	°C

3.2 Input and Output Nodes

The introduced parameters which as the input vector components consist of; the Rockwell hardness HRC, Impact toughness It, Yield strength Ys, Ultimate tensile strength Us. The output data are Austenitizing temperature Ta, and tempering temperature Tt. Therefore, the nodes in the input and output layer are 4 and 2, respectively.

3.3 The Number of Nodes and Number of Hidden Layers

An adequate number of hidden layers and the number of nodes is carried out choosing in each hidden layer by the trial-and-error approach. It is usual to start with a relatively small number of hidden units and increase it until we are satisfied with the approximation quality of the network. According to the following rules, selected in the hidden layer the number of nodes [11]:

- The maximum error of the output parameters network for testing and training patterns should be as small as possible.
- There is a perfect correlation between outputs and targets if this number is equal to 1, then the correlation coefficient should be as high as possible.

In this investigation, the one and two hidden layers' network configurations is tested in each hidden layer with an increasing number of nodes and the different activation and training function types.

3.4 Investigation of one Hidden Layer

A different activation and training functions are investigated for the hidden and output layer of one hidden layer networks. In each hidden layer, a different numbers of nodes from 12 to18 nodes are used. Tables 2, 3, 4, 5, 6 and 7 represent the regression and performance of these network for testing and training data.

Table 2: R and MSE for training functions of Conjugate Gradient

Activation Function	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
Activation Function: {tansig, purelin}	*traincgf*	12	0.000795	0.9995	0.9988	0.0026	0.9963	0.9953
		14	0.000 33	1.0000	0.9992	6.419e-5	1.0000	0.9998
		16	7.772e-5	0.9999	0.9999	0.00031	0.9994	0.9997
		18	3.203e-6	1.0000	1.0000	3.911e-6	1.0000	1.0000
	traincgp	12	0.000507	0.9999	0.9989	0.0033	0.9999	0.9875
		14	8.68e-5	1.0000	0.9999	0.000287	0.9999	0.9991
		16	4.022e-5	1.0000	1.0000	5.544e-6	1.0000	1.0000
		18	6.90e-6	1.0000	1.0000	4.364e-6	1.0000	1.0000
	traincgb	12	0.000199	0.9999	0.9996	0.000473	0.9997	0.9987
		14	1.126e-6	1.0000	1.0000	2.064e-6	1.0000	1.0000
		16	1.72e-7	1.0000	1.0000	2.372e-7	1.0000	1.0000
		18	2.402e-7	1.0000	1.0000	8.736e-8	1.0000	1.0000
	trainscg	12	0.000384	0.9998	0.9994	0.000761	0.9998	0.9982
		14	0.000237	0.9999	0.9995	0.000178	0.9999	0.9996
		16	2.09e-10	1.0000	1.0000	3.96e-10	1.0000	1.0000
		18	2.29e-10	1.0000	1.0000	2.04e-10	1.0000	1.0000

Table 3: R and MSE for training functions of Quasi-Newton

Activation Function	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
Activation Function : {tansig, purelin}	*trainbfg*	12	0.000147	0.9999	0.9998	0.000114	0.9999	0.9997
		14	0.000171	1.0000	0.9997	0.0026	0.9989	0.9920
		16	9.97e-10	1.0000	1.0000	8.635e-10	1.0000	1.0000
		18	4.78e-10	1.0000	1.0000	3.55e-10	1.0000	1.0000
	trainoss	12	0.0011	0.9993	0.9983	0.0019	0.9985	0.9969
		14	0.000525	0.9999	0.9988	0.0001057	1.0000	0.9996
		16	6.304e-6	1.0000	1.0000	9.175e-6	1.0000	1.0000
		18	1.95e-10	1.0000	1.0000	3.597e-10	1.0000	1.0000

Table 4: R and MSE for training functions of Gradient Descent

Activation Function	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
Activation Function : {tansig, purelin}	*traingd*	12	0.1499	0.7645	0.9084	0.1001	0.7960	0.8777
		14	0.1064	0.8560	0.9279	0.0762	0.8606	0.8941
		16	0.1034	0.8549	0.9230	0.0770	0.8431	0.9067
		18	0.1019	0.8392	0.9460	0.0549	0.8913	0.9438
	traingdm	12	0.1049	0.8520	0.9317	0.1103	0.8309	0.8282
		14	0.1088	0.8285	0.9443	0.0877	0.8262	0.8883
		16	0.1232	0.8330	0.8983	0.1056	0.7610	0.9025
		18	0.0936	0.8693	0.9352	0.0871	0.7998	0.9171

Table 5: R and MSE for training functions of Levenberg-Marquardt

Activation Function	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
Activation Function :{tansig, purelin}	*Trainlm*	12	0.000158	1.000	0.999	0.000204	1.000	0.999
		14	6.19e-28	1.000	1.000	4.49e-28	1.000	1.000
		16	1.63e-28	1.000	1.000	1.65e-28	1.000	1.000
		18	1.89e-21	1.000	1.000	4.16e-22	1.000	1.000
	Trainbr	12	6.713e-4	0.999	0.999	0.0014	0.999	0.995
		14	5.935e-5	1.000	0.999	2.546e-4	0.999	0.999
		16	1.52e-29	1.000	1.000	1.46e-29	1.000	1.000
		18	2.71e-17	1.000	1.000	1.04e-16	1.000	1.000

Table 6: R and MSE for training functions of Variable Learning Rate

Activation Function	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
Activation Function: {tansig, purelin}	*traingdx*	12	0.0049	0.9954	0.9943	0.0066	0.9922	0.9882
		14	0.0028	0.9984	0.9953	0.0041	0.9975	0.9897
		16	0.0017	0.9994	0.9966	0.0028	0.9974	0.9939
		18	0.0023	0.9990	0.9956	0.0016	0.9993	0.9949

Table 7: R and MSE for training functions of Resilient Back-propagation

Activation Function :{tansig,purelin}	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	*R1*	*R2*	*MSE*	*R1*	*R2*
	trainrp	12	0.0019	0.9993	0.9962	0.0030	0.9994	0.9926
		14	0.000554	0.9994	0.9994	0.0015	0.9972	0.9986
		16	0.000176	0.9999	0.9997	0.00021	0.9999	0.9994
		18	0.000158	0.9999	0.9996	0.000142	0.9999	0.9995

From Table 7, the network with 18 nodes in the hidden layer and arrangement of activation function (tansig) (purelin) function and training function (trainrp) for hidden and output layers respectively gives better performance and a correlation coefficient than another.

3.5 Investigation of Two Hidden Layers

In this section, investigated of two hidden layer networks for each layer with different activation and training functions. In each hidden layer, a different numbers of nodes from 5 to 8 nodes are used. The regression and performance of these network topologies of testing and training are presented in Tables 8, 9,10, 11, 12 and 13.

From Table 8 the performance of network with (8-5) nodes (8 is the nodes of the first hidden layer and 5 nodes in the second hidden layer) gives the better regression for testing and training than the other. The results show that the network of two hidden layer is significantly better than that one hidden layer.

Affects the number of nodes response in the one and two hidden layers of the network with different node numbers and training functions represented in the tables from 2 to 13. Selected back-propagation conjugate gradient type (trainscg) here as a training function. Compared to the present work investigated to other functions.

Figure 3 and Table 14 show examined activation functions arrangements, in order to complete this investigation with the selected training function.

It can show from Table 14 that arrangement of the activation function (tansig, tansig, purelin) gives the best performance and regressions for testing and training phases.

Table 8: R and MSE for training functions of Conjugate Gradient

Activation Function : {tansig,tansig,purelin}	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	*R1*	*R2*	*MSE*	*R1*	*R2*
	traincgf	6-7	0.0026	0.9969	0.9978	0.0022	0.9986	0.9970
		7-5	0.0013	0.9996	0.9972	0.000825	0.9990	0.9985
		7-8	0.00085	0.9993	0.9989	0.000426	0.9991	0.9996
		8-5	0.00079	0.9998	0.9984	0.000522	0.9995	0.9989
	traincgp	6-7	0.000884	0.9988	0.9994	0.000264	0.9998	0.9994
		7-5	0.000812	0.9996	0.9986	0.000374	0.9998	0.9995
		7-8	0.000728	0.9996	0.9988	0.0010	0.9993	0.9982
		8-5	0.000219	0.9998	0.9998	0.000918	0.9983	0.9991
	traincgb	6-7	0.000519	0.9994	0.9995	0.000381	0.9994	0.9996
		7-5	0.0012	0.9998	0.9973	0.000431	0.9994	0.9994
		7-8	0.000122	0.9999	0.9999	0.0017	0.9970	0.9980
		8-5	0.000928	0.9993	0.9987	0.000704	0.9999	0.9977
	trainscg	6-7	0.0013	0.9994	0.9976	0.0023	0.9958	0.9970
		7-5	0.0011	0.9998	0.9975	0.000678	0.9994	0.9986
		7-8	0.000206	1.0000	0.9995	0.000459	0.9999	0.9987
		8-5	0.000 144	0.9999	0.9997	2.355e-5	0.9999	0.9999

Table 9: R and MSE for training functions of Quasi-Newton

Activation Function : {tansig,tansig,purelin}	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	*R1*	*R2*	*MSE*	*R1*	*R2*
	trainbfg	6-7	0.000362	1.0000	0.9992	0.000521	1.0000	0.9984
		7-5	0.000184	0.9999	0.9997	0.000354	0.9999	0.9989
		7-8	0.000466	1.0000	0.9989	0.000133	0.9999	0.9996
		8-5	0.00095	0.9997	0.9981	0.000625	0.9997	0.9983
	trainoss	6-7	0.0012	0.9996	0.9975	0.000717	0.9997	0.9978
		7-5	0.0015	0.9987	0.9981	0.0013	0.9980	0.9985
		7-8	0.000141	0.9999	0.9997	0.000293	0.9999	0.9991
		8-5	0.0014	0.9995	0.9971	0.000189	0.9998	0.9997

Table 10: R and MSE for training functions of Levenberg-Marquardt.

ActivationFunction : {tansig,tansig,purelin}	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	*R1*	*R2*	*MSE*	*R1*	*R2*
	trainlm	6-7	0.000427	1.000	0.9990	0.00031	1.000	0.9990
		7-5	0.000574	0.9999	0.9988	0.000244	0.9999	0.9994
		7-8	0.000844	0.9993	0.9988	0.000163	0.9998	0.9996
		8-5	0.000179	1.000	0.9996	0.000729	0.9988	0.9989
	trainbr	6-7	0.4743	0.0000	0.0000	0.3527	0.0000	0.0000

		7-5	0.0052	0.9932	0.9963	0.0055	0.9944	0.9874
		7-8	1.22e-16	1.000	1.000	1.33e-16	1.000	1.000
		8-5	0.000477	0.9999	0.9990	0.000215	0.9999	0.9994

Table 11: R and MSE for training functions of Variable Learning Rate

Activation Function: {tansig,tansig,purelin }	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
	traingdx	6-7	0.0078	0.9951	0.9876	0.0084	0.9937	0.9822
		7-5	0.0075	0.9937	0.9899	0.0045	0.9973	0.9881
		7-8	0.0059	0.9979	0.9882	0.0023	0.9985	0.9964
		8-5	0.0054	0.9971	0.9907	0.0074	0.9973	0.9793

Table 12: R and MSE for training functions of Gradient Descent

Activation Function : {tansig,tansig,purelin}	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
	traingd	6-7	0.1650	0.7405	0.8872	0.0914	0.8255	0.8984
		7-5	0.1114	0.8467	0.9087	0.0656	0.8790	0.9048
		7-8	0.0993	0.8997	0.8793	0.1089	0.7674	0.8646
		8-5	0.1276	0.8258	0.8955	0.0931	0.8038	0.8927
	traingdm	6-7	0.1689	0.7353	0.8816	0.1246	0.7331	0.8632
		7-5	0.1479	0.8280	0.8409	0.1070	0.8018	0.8369
		7-8	0.0915	0.8859	0.9149	0.0847	0.8605	0.8589
		8-5	0.0929	0.8856	0.9114	0.0912	0.8642	0.8369

Table 13: R and MSE for training function of Resilient Back-propagation

Activation Function: {tansig,tansig,purelin }	Training Function	Node No.	Training data (80%)			Testing data (20%)		
			MSE	***R1***	***R2***	***MSE***	***R1***	***R2***
	trainrp	6-7	0.0028	0.9991	0.9944	0.0057	0.9972	0.9861
		7-5	0.0032	0.9977	0.9951	0.0021	0.9994	0.9930
		7-8	0.0018	0.9987	0.9973	0.0014	0.9990	0.9979
		8-5	0.0024	0.9983	0.9963	0.0017	0.9980	0.9977

Table 14: Regression & MSE with different arrangements training function of (trainscg) with activation functions of (4-8-5-2) network

Trainscg Training Function	Activation Functions Arrangements				
	tansig, purelin, purelin	*tansig, tansig, purelin*	*tansig, tansig, tansig*	*purelin, tansig, tansig*	*tansig, purelin, tansig*
MSE (train)	0.0087	0.000144	0.0025	0.0343	0.0080
MSE (test)	0.0072	2.355e-5	0.000132	0.0158	0.0023
R1 (train)	0.9929	0.9999	0.9999	0.9773	0.9899
R1 (test)	0.9919	0.9999	0.9999	0.9976	0.9991
R2 (train)	0.9879	0.9997	0.9941	0.9482	0.9946
R2 (test)	0.9837	0.9999	0.9997	0.9424	0.9935

3.6 Suggested Network

From the analysis above, it can be noted that the training function (trainscg) arrangements for different neural networks, with activation functions (tansig, tansig, purelin) for the two and output layers, respectively gives the best correlation coefficients and (MSE) for both testing and training than the other. Therefore, for the present study can be selected this network as a suggested network. Figure 1 represented the performance of the different activation functions each of (4-8-5-2) network with (trainscg) training function, also shown the best one is (tansig, tansig, purlin). Figure 2 shown the comparison performance between the best one and two hidden layers. Figure 3 represents the suggested network configuration. Figures 4, 5, 6 and 7 represents the analysis of regression between the output of neural network and the corresponding target for testing and training data respectively, for Austenitizing temperature (Ta), and tempering temperature (Tt). Outputs are plotted versus the targets in these Figures. The broken line indicates the perfect fit and the solid line indicates the best linear fit (output equals target).

Figures 8 and 9 show the neural networks behavior to predict overall austenitizing temperature (Ta), and tempering temperature (Tt) for the training data set respectively.

Similar Figures 10 and 11 are show the predicted and actual values of output parameters plotted, overall austenitizing temperature (Ta), and tempering temperature (Tt) for testing data set respectively. It is can be noted that the predicted and actual values are close to each other, which lead to conclude that the ANN proposed model has high levels of accuracy for both testing and training data of prediction of (Ta) and (Tt).

3.7 Computer Program

The computer program contains three steps as follows:

- The first step is the generalization processes of the back-propagation of Artificial Neural Network that is coded in Matlab program. Figure 12 shown the structure of the Artificial Neural Network program. The main variables are stored in Matlab by the cell multidimensional arrays whose elements are copies of other arrays, and description of the ANN is saved and extracted in a separate file. Suitable values of the biases and weight as a results of this step.
- The second step is the Matlab function that is coded in Matlab program. From step 1 extracted this function uses the network parameters to put the selected model in its operating mode.
- The third step is the Graphical User Interface is coded by Matlab program. From step 2 extracted this program uses the

function to put the selected model in its operating mode as shown in Figure 13.

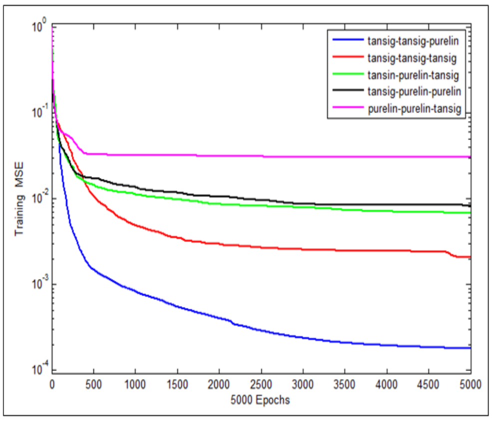

Fig. 1: Comparison of suggested network performance of activation function

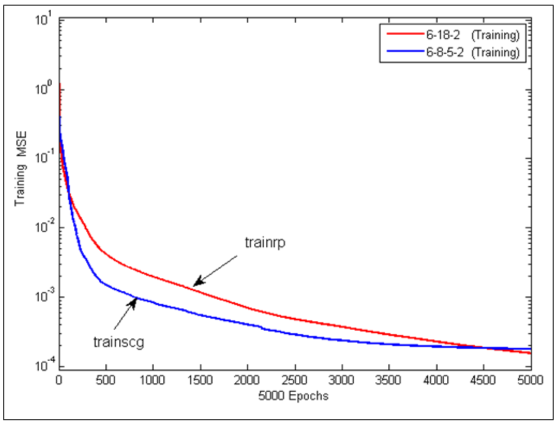

Fig. 2: Comparisons of network performance between the best one and two hidden layers'

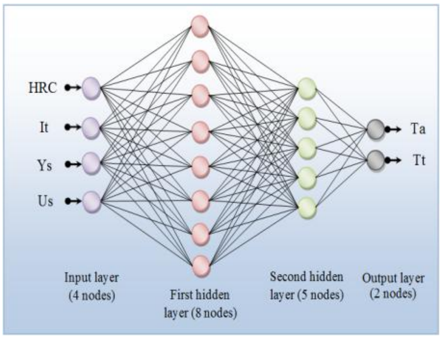

Fig. 3: The Configuration of the suggested ANN (4-8-5-2)

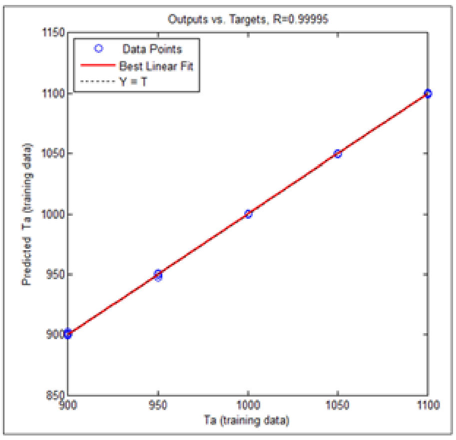

Fig. 4: Training Ta Regression of the Proposed Network

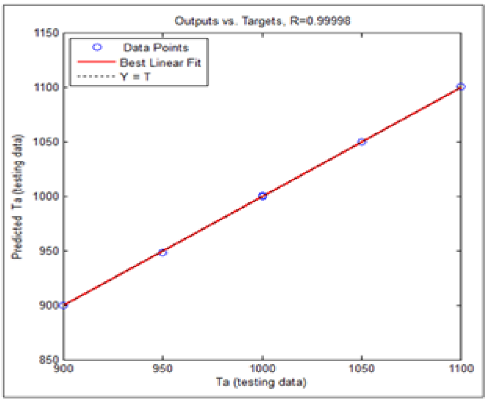

Fig. 5: Testing Ta Regression of the Proposed Network

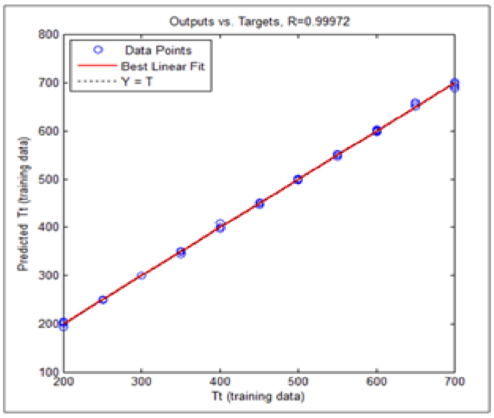

Fig. 6: Training Tt Regression of the Proposed Network

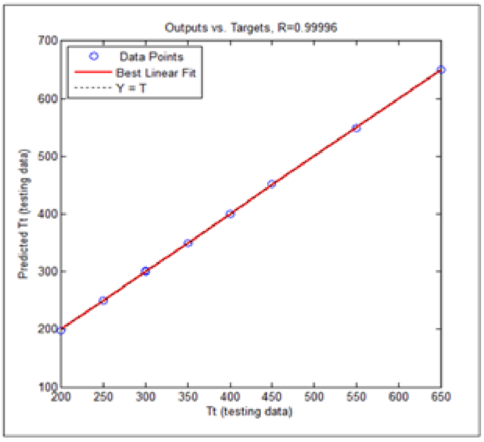

Fig. 7: Testing Tt Regression of the Proposed Network

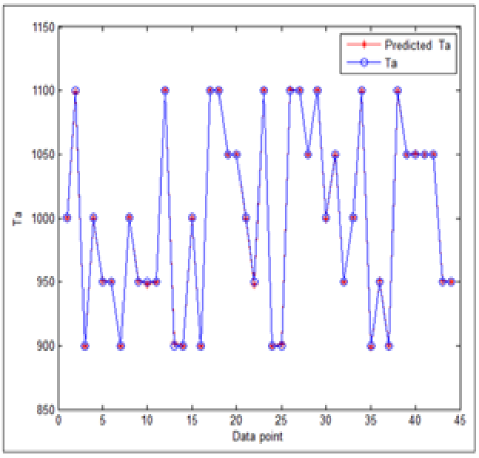

Fig. 8: Training Behavior of Predicted Overall Austenitizing temperatures

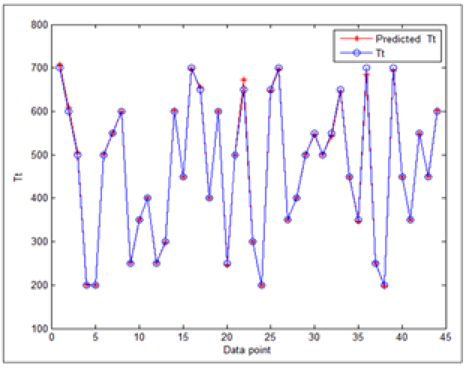

Fig. 9: Training Behavior of Predicted Overall Tempering temperatures

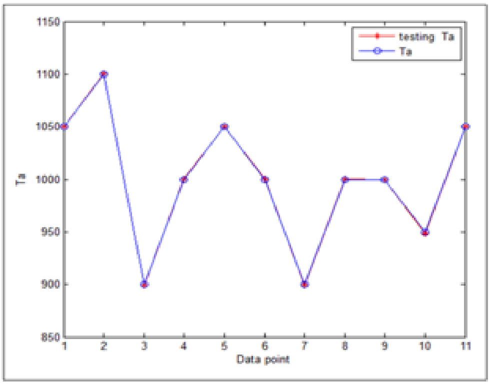

Fig. 10: Testing Behavior of Predicted Overall Austenitizing temperatures

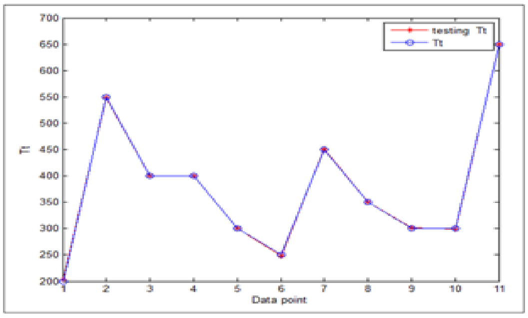

Fig. 11: Testing Behavior of Predicted Overall tempering temperatures

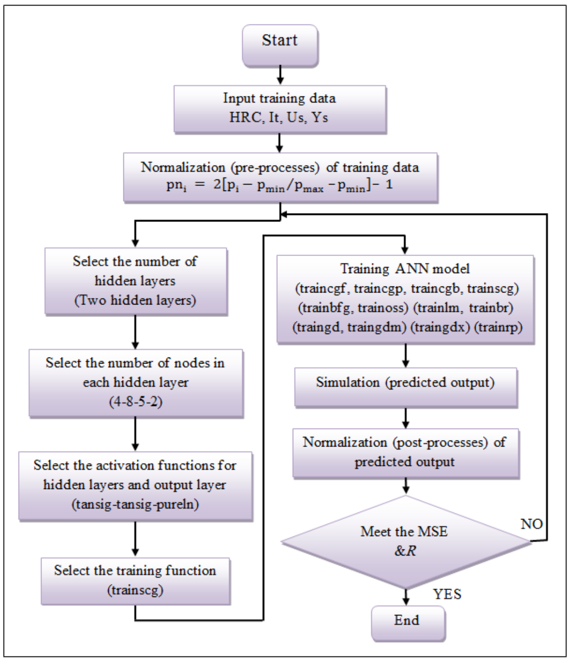

Fig. 12: The Structure of the Artificial Neural Network Program

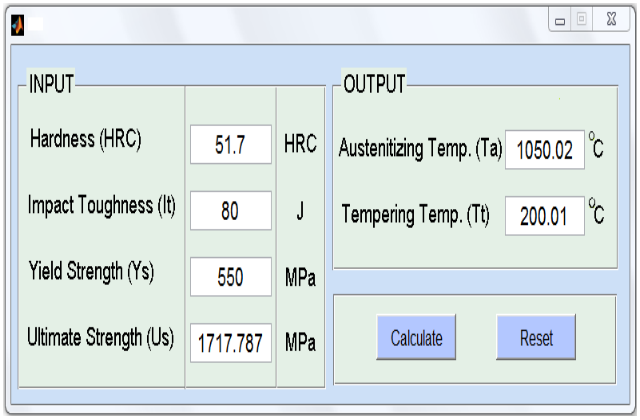

Fig. 13: Steps of the Graphical User Interface of Neural Network Program

4. Results and Discussion

Computer programs that are coded in Matlab language are used to develop the Multi-Output Artificial Neural Network model. Linear and nonlinear regression analysis using statistical software (Data fit) involved to develop the best mathematical models are presented to predict austenitizing and tempering temperature compares with Matlab program.

4.1 Multiple Linear Regression Analysis Model

The regression procedure was employed for developing the mathematical models; the first step, multiple linear regression analysis techniques were used. The mechanical properties of the experimental results of martensitic stainless steel samples were used in this model as input variables such as hardness, impact energy, yield and tensile strength. Separate models were developed for heat treatment conditions (Austenitizing and tempering temperature). The multiple linear regression analysis was performed using Statistical software (Data fit RC 148, 2008) to generate a model using the least squares method to fit data through a set of observations. The number of functions was defined to describe the relationships between the input and each output variable.

The functions of linear regression model were initially defined by Y= f (HRC, It, Ys, Us) according to the equation (1) [12]:

$$Y = a_o + ax_1 + bx_2 + cx_3 + \ldots.. + nx_m \quad (1)$$

Where a_o is the free term of the regression equation. (a, b, c, ….. n) are coefficients in linear terms.

The mathematical models that determined by the above analysis are represented below:

Austenitizing Temperature = (758.510172) – (0.905466987) (HRC) + (1.093313339) (It) – (6.27E-02) (Ys) + (0.384543051) (Us) (2)

Tempering Temperature = (500.8754918) – (2.880372275) (HRC) + (1.192089984) (It) +(0.544228309) (Ys) +(0.169287202) (Us) (3)

4.2 Multiple Nonlinear Regression Analysis Model

The multiple nonlinear regression procedures were used for developing the mathematical models to predict Austenitizing and Tempering Temperature. The second order polynomial representing the response for "n" factors are given by equation (4) [13]:

$$Y = a_o + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} a_{ii} x_{ii}^2 + \sum_{i<j}^{n} a_{ij} x_i x_j \quad (4)$$

Where a_o is the free term of the regression equation. a_1, a_2, a_3, a_4, a_5 and a_6 are coefficients in linear terms. a_{11}, a_{22}, a_{33}, a_{44}, a_{55}, and a_{66} are quadratic terms and the coefficients a_{12}, a_{13}, a_{14}, a_{15}, a_{16}, a_{23}, a_{24}, a_{25}, a_{26}, a_{34}, a_{35}, a_{36}, a_{45}, a_{46}, and a_{56} are coefficients interaction terms. Statistical software (Data fit RC 148, 2008) program was employed to calculate the values of these coefficients. The mathematical models that determined by the above analysis are represented below:

Austenitizing Temperature = – (2051.773065) + (30.53528934) (HRC) + (22.10365287) (It) + (2.848325703) (Ys) + (8.289644551) (Us) + (1.159318915) (HRC^2) – (0.054127166) (It^2) – (8.91E-04) (Ys^2) + (9.02E-04) (Us^2) + (3.95E-02) (HRC) (It) – (2.95E-02) (HRC) (Ys) – (0.156423196) (HRC) (Us) – (8.71E-03) (It) (Ys) – (1.79E-02) (It) (Us) – (2.63E-03) (Ys) (Us) (5)

Tempering Temperature = – (1486.386696) – (139.240141) (HRC) + (37.18283173) (It) + (2.888351357) (Ys) + (17.47920735) (Us) + (2.208059056) (HRC^2) – (6.14E-03) (It^2) + (1.96E-03) (Ys^2) + (5.25E-03) (Us^2) + (0.311734233) (HRC) (It) + (0.113209079) (HRC) (Ys) – (0.287336394) (HRC) (Us) – (2.33E-02) (It) (Ys) – (3.47E-02) (It) (Us) – (1.44E-02) (Ys) (Us) (6)

4.3 Comparisons between the Linear and Nonlinear Regression Analysis Results Model

Table 15 shows the experimental data against the predictions linear and nonlinear regression analysis results by using eleven datasets. Table 15 shows that the error maximum between experiment and the predicted linear results for the prediction of austenitizing temperature is 10.7812 % and the mean error rate is 3.6649 %. While the maximum error between experimental and nonlinear regression analysis results is 7.4441 % and the mean error rate is 2.5318 %. Moreover, Table 16 shows that the error maximum between experiment and the predicted linear results for the prediction of tempering temperature is 29.0091 % and the mean error rate is 15.697 %. While maximum error between experimental and nonlinear regression analysis results of tempering temperature is 39.04536 % and the mean error rate is 12.08883 %.

A comparison of the relative standard error for linear and nonlinear regression analysis shows that the nonlinear predictions are superior to the linear analysis for all the input mechanical properties. Therefore, nonlinear regression analysis provides an overall reasonable to define the objective function.

The plot of the experimental data against the predictions linear and nonlinear regression analysis results is shown in the Figures 14 and 15 for testing austenitizing and tempering temperature.

Table 15: Comparison between experimental, Linear and Nonlinear regression analysis results of austenitizing temperature

Experimental Results	Linear Regression	Error %	Nonlinear Regression	Error %
1050	1009.404	3.8663	1023.856	2.4899
1100	981.4066	10.7812	1018.115	7.4441
900	882.3231	1.9641	889.4762	1.1693
1000	986.7937	1.32063	1005.615	0.5615
1050	1030.02	1.90286	1057.959	0.758
1000	1024.39	2.439	1019.123	1.9123
900	859.3434	4.5174	875.0711	2.7699
1000	1011.098	1.1098	1015.025	1.5025
1000	1036.408	3.6408	1028.569	2.8569
950	994.6287	4.69776	990.2234	4.2340
1050	1007.225	4.07381	1027.415	2.15095
Mean error rate %	3.6649		2.5318	

$$* \text{percentage error} = \left|\frac{\text{Experimental} - \text{predicted value}}{\text{Experimental}}\right| \text{x}100$$

$$* \text{mean error rate} = \sum_{i=1}^{n} \text{percentage error}/n,$$

Where, n = 11

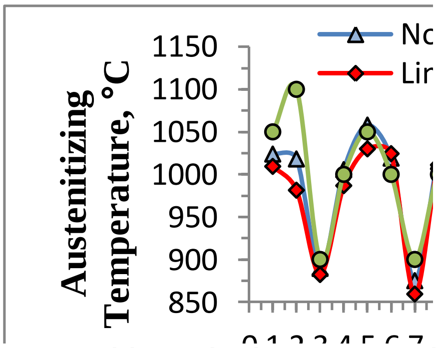

Fig. 14: The experimental, linear and nonlinear regression analysis results of testing austenitizing temperature

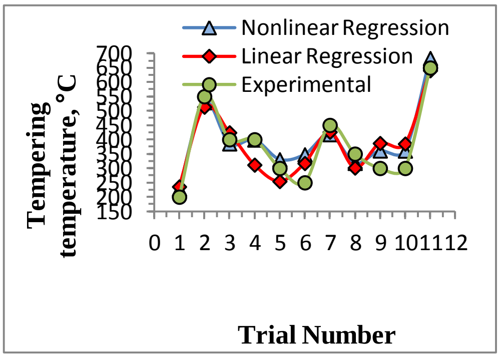

Fig. 15: The experimental, linear and nonlinear regression analysis results of testing tempering temperature

Table 16: Comparison between experimental, Linear and Nonlinear regression analysis results of tempering temperature

Experimental Results	Linear Regression	Error %	Nonlinear Regression	Error %
200	235.7275	17.86375	228.3187	14.15935
550	513.5173	6.63322	529.0312	3.81251
400	424.2353	6.05883	385.6721	3.581975
400	311.6268	22.0933	399.1881	0.202975
300	254.4996	15.1668	330.388	10.12934
250	317.2229	26.8892	347.6134	39.04536
450	426.292	5.26845	417.7829	7.159356
350	301.4481	13.87198	317.7952	9.201372
300	387.0273	29.0091	361.0238	20.3413
300	385.0775	28.3592	360.72	20.24
650	640.5458	1.454493	683.1737	5.10365
Mean error rate %	15.697		12.08883	

4.4 Comparisons between the ANN and Nonlinear Regression Analysis Models

Table 17 shows a comparison between the experimental and predicted ANN and nonlinear regression analysis results using eleven datasets.

Table 17 shows that the maximum error between experiment and the predicted ANN results for prediction austenitizing temperature is 0.140064 % and the mean error rate is 0.032947 %. While the maximum error between experimental and nonlinear regression analysis results is 7.4441 % and the mean error rate is 2.5318 %.

Moreover, Table 18 shows that the maximum error between experiment and the predicted ANN results for prediction

tempering temperature is 1.45285 % and the mean error rate is 0.320189 %. While maximum error between experimental and nonlinear regression analysis results is 39.04536 % and the mean error rate is 12.08883 %.
It can be concluded that from the above mentioned, the artificial neural network is a more accurate prediction system than nonlinear regression analysis for predicting austenitizing and tempering temperature. Therefore, this work used artificial neural network models to define the objective function.
The plot of the experimental data against the artificial neural network predictions and nonlinear regression analysis results is shown in the Figures 16 and 17 for testing austenitizing and tempering temperature.

Table 17: Comparison between experimental, predicted ANN model and nonlinear regression analysis results of austenitizing temperature

Experimental Results	Predicted ANN	Error %	Nonlinear Regression	Error %
1050	1049.86	0.01334	1023.856	2.4899
1100	1100.673	0.06119	1018.115	7.4441
900	899.7311	0.029878	889.4762	1.1693
1000	1000.16	0.016	1005.615	0.5615
1050	1049.865	0.012857	1057.959	0.758
1000	1000.097	0.0097	1019.123	1.9123
900	899.7342	0.029534	875.0711	2.7699
1000	1000.458	0.0458	1015.025	1.5025
1000	999.9726	0.00274	1028.569	2.8569
950	948.6694	0.140064	990.2234	4.2340
1050	1049.986	0.00134	1027.415	2.15095
Mean error rate %	0.032947		2.5318	

Table 18: Comparison between experimental, predicted ANN model and nonlinear regression analysis results of tempering temperature

Experimental Results	Predicted ANN	Error %	Nonlinear Regression	Error %
200	202.9057	1.45285	228.3187	14.15935
550	548.9291	0.19471	529.0312	3.81251
400	399.9829	0.004275	385.6721	3.581975
400	399.7335	0.066625	399.1881	0.202975
300	300.2411	0.080367	330.388	10.12934
250	247.7523	0.89908	347.6134	39.04536
450	450.9974	0.221645	417.7829	7.159356
350	349.9289	0.02032	317.7952	9.20137
300	301.3199	0.43997	361.0238	20.34127
300	299.601	0.133	360.72	20.24
650	650.0601	0.00925	683.1737	5.10365
Mean error rate %	0.320189		12.08883	

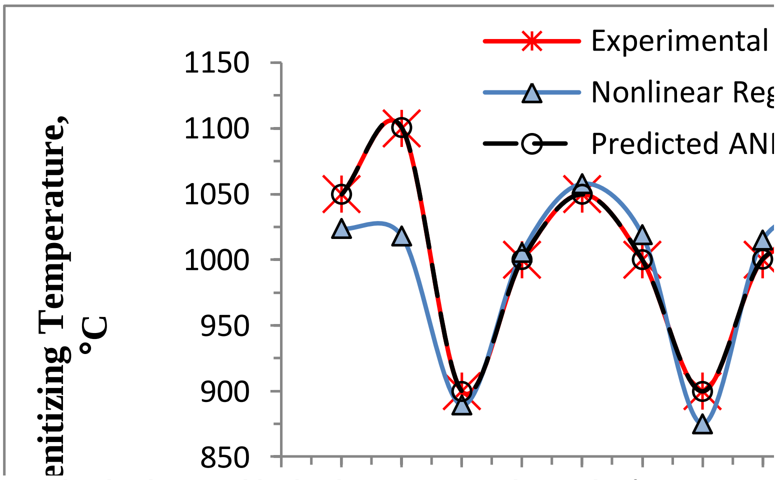

Fig. 16: The experimental predicted ANN model and nonlinear regression analysis results of testing austenitizing temperature

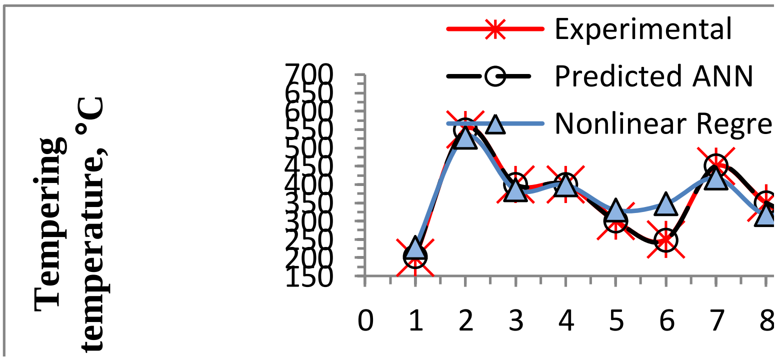

Fig. 17: The experimental, predicted ANN model and nonlinear regression analysis results of testing tempering temperature

5. Modeling Results

Results obtained show the high ability of artificial neural networks from the given range of input data to predict heat treatment temperature (Austenitizing and Tempering Temperature).

Inform about low deviation ratio of the correct execution of the testing and training and the correlation coefficient over 90 %, small differences in the relation between computed by measured values experimentally and ANN model. The vectors of uniform distribution in every set indicated that a good ability of the networks to results generalization.

Received results also have confirmed the correctness of the artificial neural network usage as possible the simulating tool for the application in the area of engineering material for mechanical properties prediction. Heat treatment applied with success for stainless steels it gives the chance on the effective application for different stainless steel grades or even for the different types of engineering materials.

This study investigates the ability to using multiple outputs Artificial Neural Network model that was built with Matlab package accurately to predict the quenching and tempering temperatures for martensitic stainless steel. Also, linear and nonlinear regression analyses (using Data fit package) were used to estimate the mathematical relationship between quenching and tempering temperatures with hardness, tensile properties and impact energy of martensitic stainless steel have been investigated as a function of mechanical properties in order to achieve the suitable heat treatment temperature.

6. Conclusions

The most important conclusions drawn from the present study that is the best training function that found in one and two hidden layers is [trainrp and transcg] respectively. The arrangement of activation function [tansig, tansig, purelin] is found to give a maximum regression and minimum mean square error for both training and testing phases.

The ANN model with two hidden layers significantly improves the performance of the network rather than a single hidden layer. In this investigates the configuration of (8-5) (8 is the nodes of the first hidden layer and 5 nodes in the second hidden layer) is proved to be very efficient to predict the austenitizing and tempering temperature.

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