Mechanical Properties Control Of Low And Medium Carbon Steel Using Feed Forward Neural Networks

Mohammed J Kadhim, Mohanned M. Hessian, and Alaa Abd Al-Salam Naji

Department of Production Engineering and Metallurgy, University of Technology, Baghdad

Abstract

Two feed forward multilayer neural network (FFMNN) architecture have been constructed. The first model has two hidden layers, 20 neurons for first layers and 30 neurons for second layers. The first model utilized to control the mechanical properties (yield strength, tensile strength and hardness) which are the inputs to this model. The model gives the carbon percentage and the heat treatment type and temperature as response to the required mechanical properties. The second model is implemented to predict the effect of carbon, quenching and tempering temperature on mechanical properties of both tensile strength and hardness of low and medium carbon steel. It has two hidden layers, 30 neurons for first layers and 60 neurons for second layers. In addition, the effect of different carbon percentages and heat treatment temperature for quenching were studied on the mechanical properties of low to medium carbon steel. The results of Vickers hardness showed that hardness, yield strength and tensile strength were increased with increasing the carbon percentage, quenching temperature and decreasing the tempering temperature. The neural networks models showed good agreements with experimental data. The correlation coefficients for the first model versus the experimental data are 0.9917, 0.9782 and 0.9954 for yield strength, tensile strength and Vickers hardness respectively. Higher correlation coefficients were obtained for the second modelling

1 INTRODUCTION

The selection of optimum material properties is an important factor for the design and production operations. These properties can be controlled by the addition of alloying elements and selection of the suitable heat treatments. The most materials used in the manufacturing, structure of buildings, car bodies etc. are plain carbon steels. The carbon steel is an alloy based on iron and carbon with specific amount of manganese, silicon, copper, sulphur and phosphor as the main alloying elements to obtain the desired properties satisfying the engineering applications[1]. The low carbon steels also called mild steel that have composition of 0.05 to 0.25% C. They are preferred to be used in many applications. They have low cost and easy to shape. They are not hard as compared with higher-carbon steels. The surface hardness can be raised effectively by carburizing. Medium carbon steels have composition of 0.25 to 0.54% C. They are strong and ductile with high wear properties[2]. The applications of low and medium carbon steels are in many fields such as spacecraft, nuclear reactors and turbine blades of jet engines. Due to the ferromagnetic properties of iron, some carbon steel alloys find important applications where their responses to magnetism is very important such as applications of electric motors and transformers [3].

Hardness is a mechanical property that measures the ability of a material to resist indentation and it is closely related to the material's strength. Hardness tests are considered as a useful tool for the evaluation of materials and quality control of manufacturing processes in research and development work. It gives an indication of materials properties such as strength, ductility and wear resistance. There is a wide range of different hardness tests; one of the most popular methods is Vickers hardness [4].

During the tensile test, the sample subjects to a controlled uniaxial tension until breakage. The maximum elongation, reduction in area, and tensile strength can be measured after the sample has been broken. Therefore, the properties such as yield strength, Young's modulus, strain-hardening characteristics and Poisson's ratio can also be calculated [5].

Murugan [6] studied the influence of mechanial properties on medium carbon steel steels. The mechanical properties were increased with increasing in tempering temperature. Ceschini et al. [7] studied the relationship among the microstructural features, the hardness and the tensile strength of A357 alloy. Busby [8] considered the relationship between yield strength and hardness measurement for both irradiated austenitic and ferritic stainless steels. The correlation for each alloy system has been developed. Adnan [9] studied the effect of cooling rate on the mechanical properties. Quenching and tempering processes were applied on AISI 4340 high strength alloy steel to study the yield strength, tensile strength, hardness, reduction in area, elongation and strain hardening by Lee [10]

The artificial neural networks (ANNs) are a mathematical tool used in prediction of complicated and nonlinear problems [11]. It consists of one or more inputs and outputs. An ANNs is operated by utilizing a high number of parallel attached simple arithmetic units [12]. Many researchers have applying ANNs to predict the material properties.[13] established a neural network model to prophesy linkage between a mechanical property (hardness) of the aluminum alloys with the alloying elements. [14] developed a new way that utilized neural networks as model to prognosis yield strength for various alloys (aluminum alloy, Cr steel, medium carbon steel and low carbon steel). [15] studied the effect of density and heat treatment influence on the strength and hardness for the powder metallurgy steel by artificial intelligence tools.

In this work the artificial neural networks has been built to model and control the mechanical properties of low and medium carbon steels as a response to the heat treatment and the additive of alloying elements.

2 Strengthening Mechanism and Experimental Work of Steels

Increase in manufacturing processes and specific requirements are applied to produce good quality products. The strengthening mechanisms are the most method used to increase mechanical properties of alloys. Strength can be defined as a plastic deformation taken place with large numbers of dislocations that move and multiply leading to macroscopic deformation [2]. To rising the mechanical properties (hardness, yield strength and tensile strength) need to inhibit the mobility of dislocations. There are six methods can be utilized to hindered movement of dislocations. These are heat treatment, work hardening, solid solution hardening, grain boundary strengthening, dispersion hardening and precipitation hardening [1].

In order to achieve the aim of this work to correlate the mechanical properties of the low and medium carbon steel ,two ANNs models have been built up. The first model is utilized to control the mechanical properties as responses to the %C and heat treatments. The second model is implement to give the desired %C and heat treatment procedure that produce the low and medium carbon steels mechanical properties which satisfy the application requirements given in the design stage. The flow chart that describes the modeling procedure is shown in Figure 1.

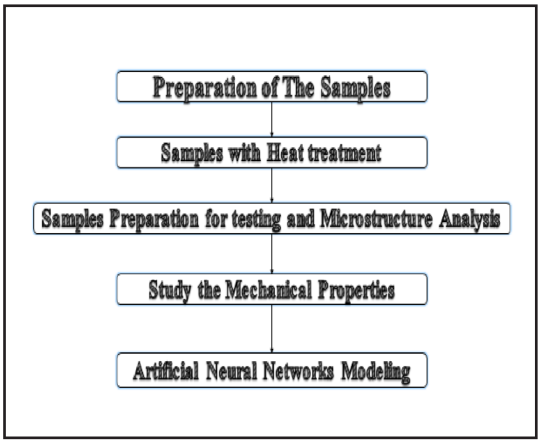


Figure 1.Modeling procedure flow chart of ANNs.

In this study, the tensile samples prepared according to ASTM E 8.The quenching and tempering temperatures were utilized to treat the samples. The quenching temperatures applied to the samples having 0.1, 0.25 and 0.5 C %are850, 910 and 950 o C respectively. After holding at one hour, the samples quenched in water. On the other hand, the tempering process were heated at different temperatures (300, 500 and 750 ^{o}C) and holdingat these temperatures for one hour and then cooled in air. In the two processes (quenching and tempering), phase transformations are occurred. In quenching process the austenite transformed to martensite and some ferrite. While in tempering process, temper martensite and ferrite were produced. The formation of martensite is led to increase the mechanical properties(hardness, yield and tensile strength) of the low and medium carbon steel.

3 .Artificial neural networks (ANNs) model

The feed forward neural networks has been trained using back-propagation algorithm. The proposed feed forward neural networks models have two hidden layers. As mentioned previously, two feed forward neural networks models have been constructed.

The first model that used to control the mechancial properties(yield strength, tensile strength and vickers hardness as inputs), where as, the outputs are %C, quenching temperature and tempering temperature. The model has two hidden layers (30 neurons for first layers and 60 neurons for second layers). While, the second model that implement to predicted the effect of %C and heat treatment (%C), quenching temperature and tempering temperature as input)and the outputs are yield strength, tensile strength and Vickers hardness. The second model has also two hidden layers (20 for first layers and 30 for second layers). Figures2 and 3 showthe ANNsmodels. The proceduresto construct the models consist from two phases. The first phase is to train the network model and the second phase is to validate the network model with data, which is not used for training.

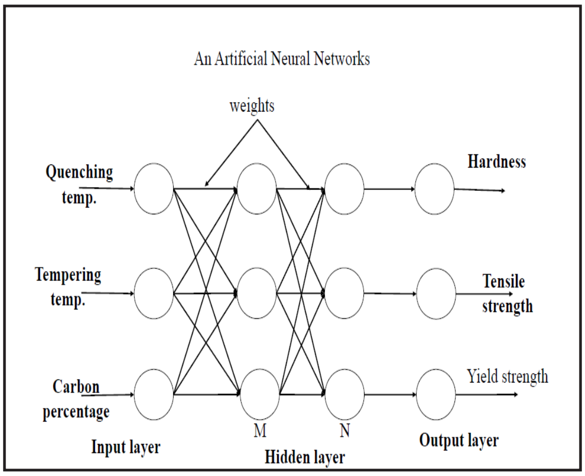


Figure 2. Artificial neural networks for first model.

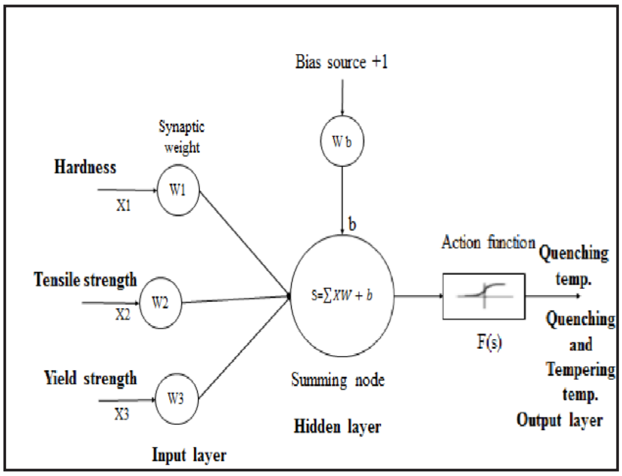
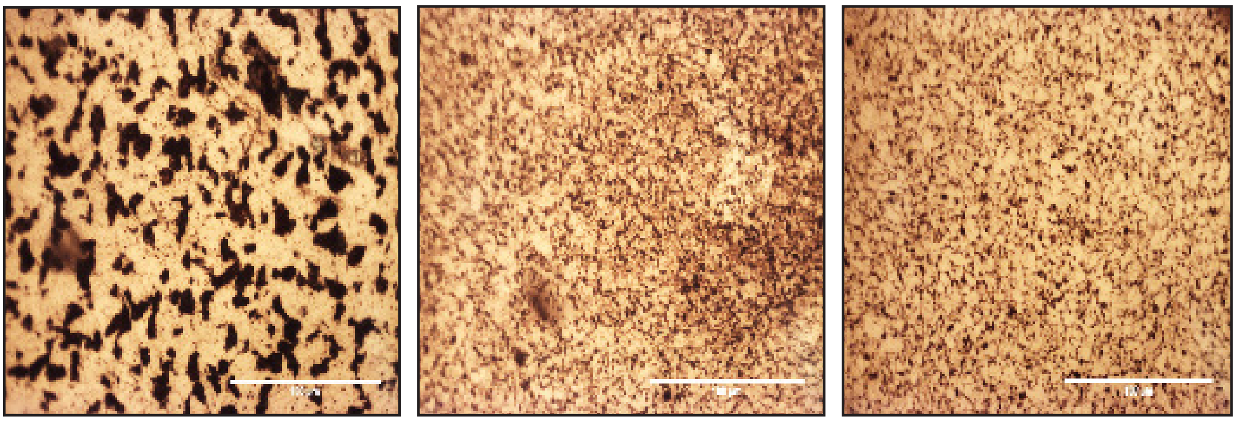


Figure 3. Artificial neural networks for second model.

4.Result and Analysis

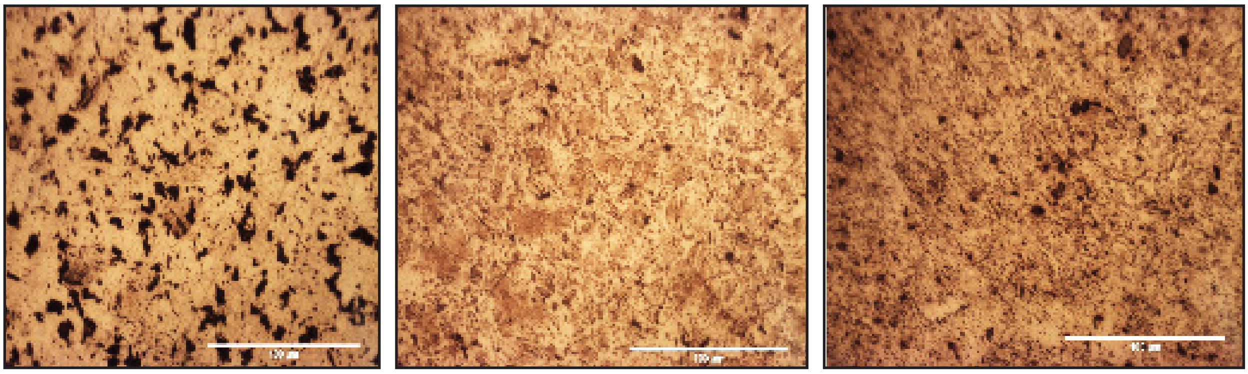
The result of heat treatments showed increase in mechanical properties of quenching process due to martensite phase(M),It is considered as the hard phase compared with initial two phases ferrie (α) and prealite (P) with different amounts. This is due to different carbon percentages appeared and some amount of ferrite formation. After tempering at different temperatures, the microstructures are tempere martensite (TM) and ferrite as shown in Figure 4.



As received

Quenching at 950 °C
0.1% carbon

Tempering at 750 °C

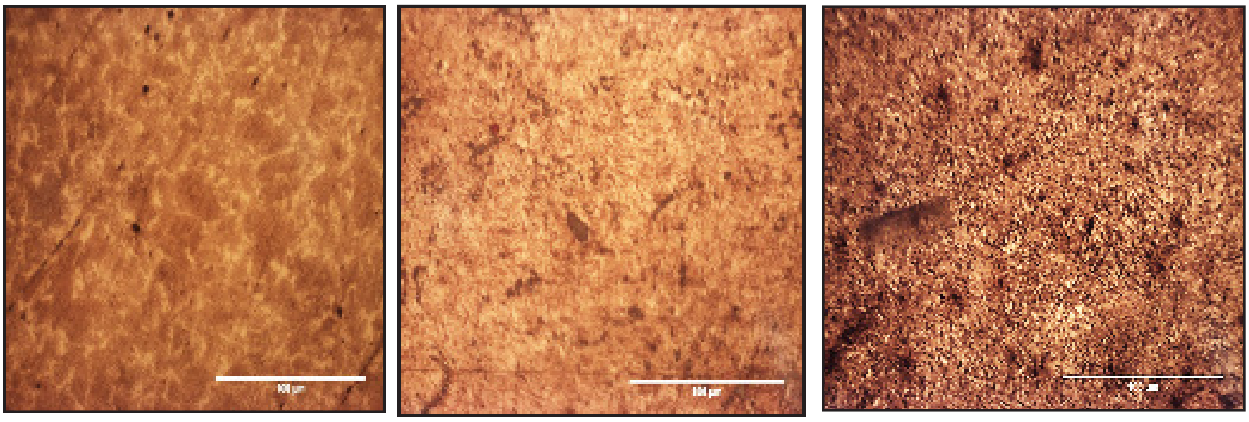


As received

Quenching at910 ^{o} C

0. 25% carbon

Tempering at 500 ^{o} C



As received

Quenching at 850 ^{o} C

0. 5% carbon

Tempering at 300 ^{o} C

Figure 4.Microstructure of the samples.

The proposed of two model ANNs will corelate the heat treatment parameters and the carbon persentages of low and medium carbon steel with the hardness.

The NNs models arefeeda forward neural network which is developed using back propagation based on gradient descent learning algorithm. During training of the two models, the network runs repeatedly with different neurons, until the output is satisfactorily accurate. The Matlab software was used for training, learning and regression curves of best modelsas shown in Figures5,6 and 7 recpestivly.For the first model, itappears that the best validationsare 4033.664 at epoch 3, gradient was 7.1433 at epoch 9 and regression was 0.97806 recpestivly. While, for the sceond modelwhich are shown in Figure 8, 9 and 10 recpestivly, the best validationsare472.0791 at epoch 2, gradient was 9.2374 at epoch 5 and regression was 0.99254 recpestivly.

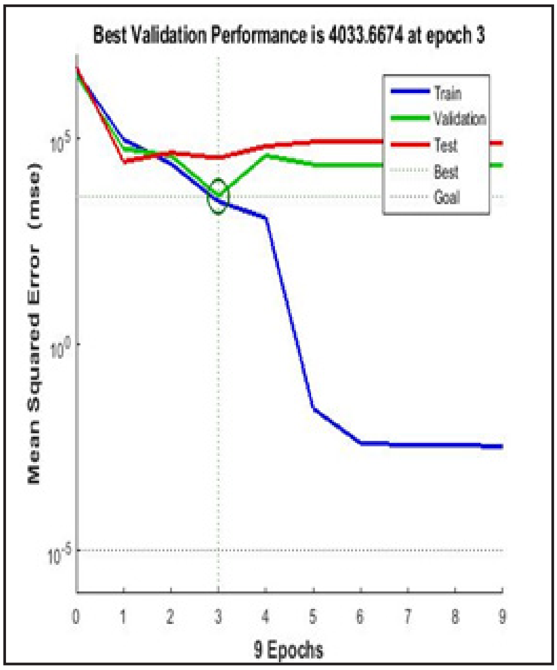


Figure 5.The training performance of ANNs.

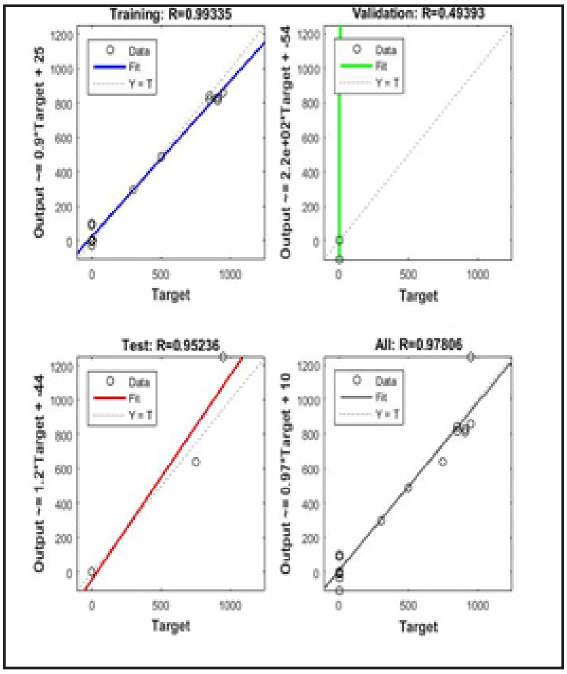


Figure 7.The regression plot of ANNs.

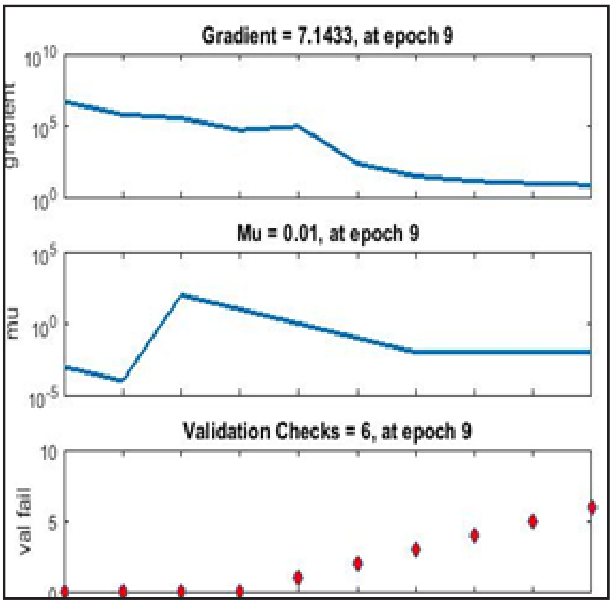


Figure 6.The training state of ANNs

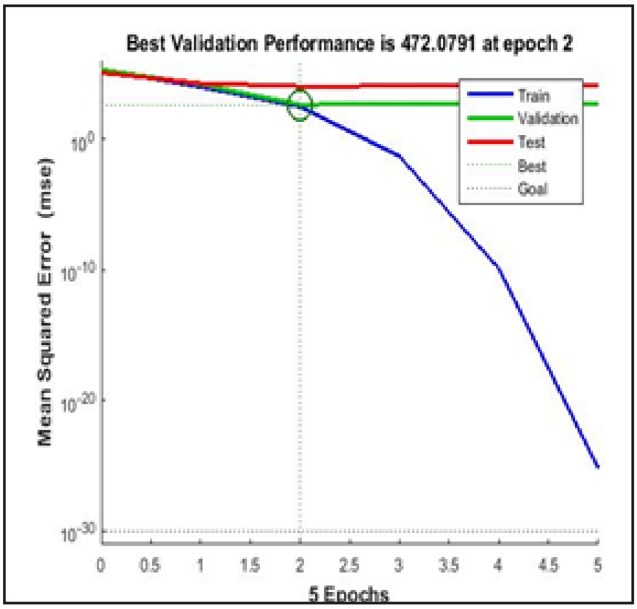


Figure 8.The training performance of ANNs

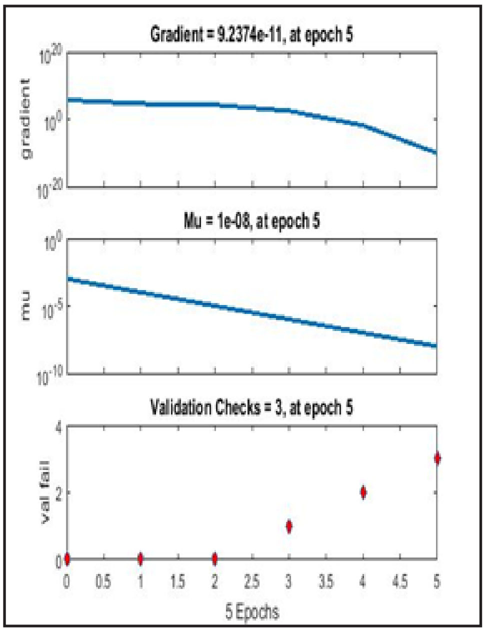


Figure 9.The training state of ANNs.

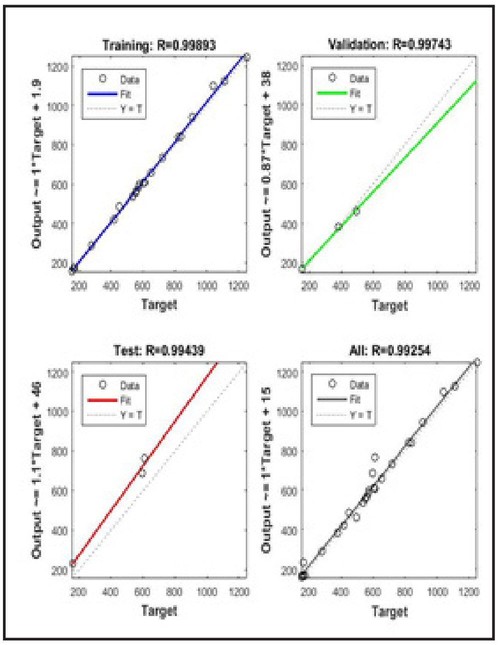
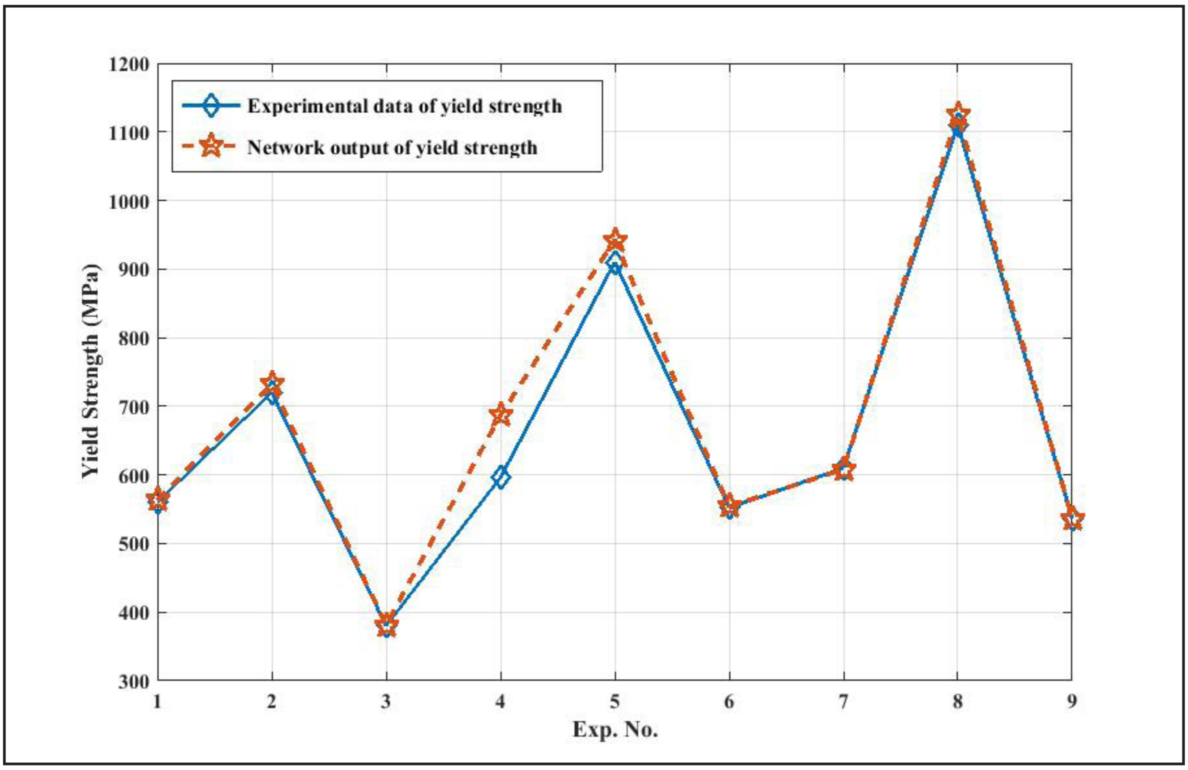


Figure 10.The regression plot of ANNs.

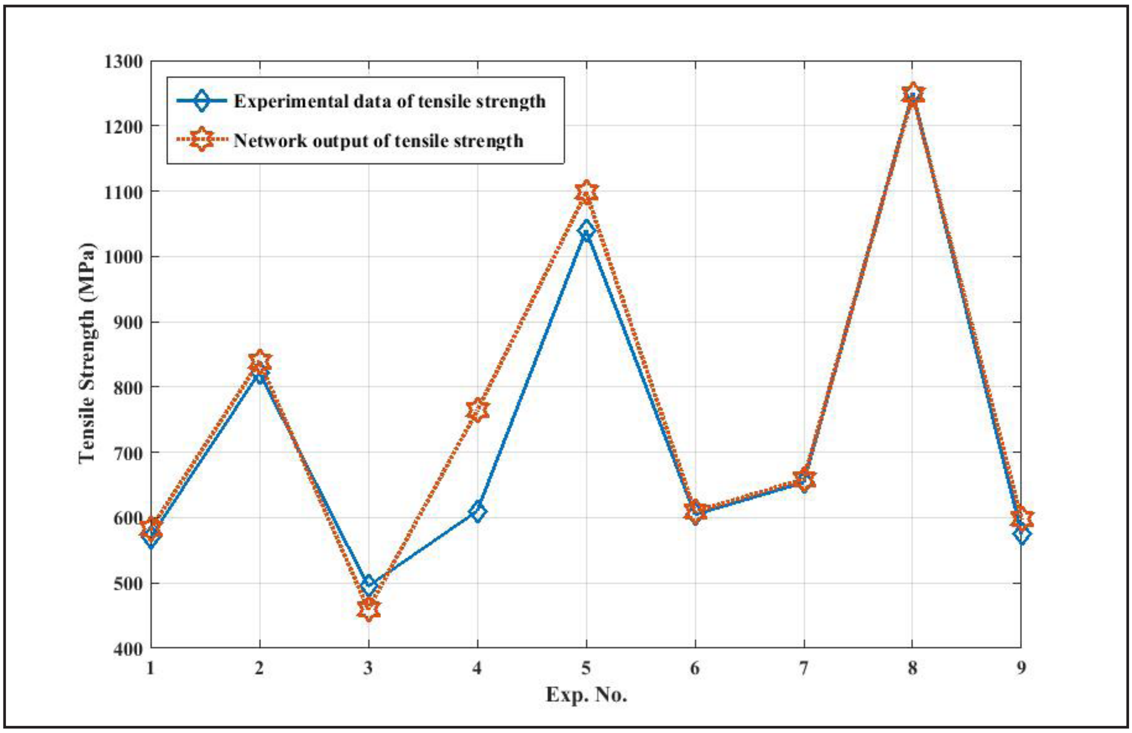
The analyses of the two modellsshow that the ANNs model can be a good predicted of mechanical properties of low and medium carbon steels as shown in Figures 11 and 12. They show the artificial neural networks output vs. experimental data for first and second model respectively.

The correlation coefficients for the three responses of the first model versusthe experimental data are 0.9917, 0.9782 and 0.9954 for yield strength, tensile strength and Vickers hardness, respectively.The sceond model have0.99122, 0.9944 and 0.9978 for %C, quenching and tempering temperature respectively.



Experimental data of yield strength
Network output of yield strength
Yield Strength (MPa)
Exp. No.

(A)



Experimental data of tensile strength
Network output of tensile strength
Tensile Strength (MPa)
Exp. No.

(B)

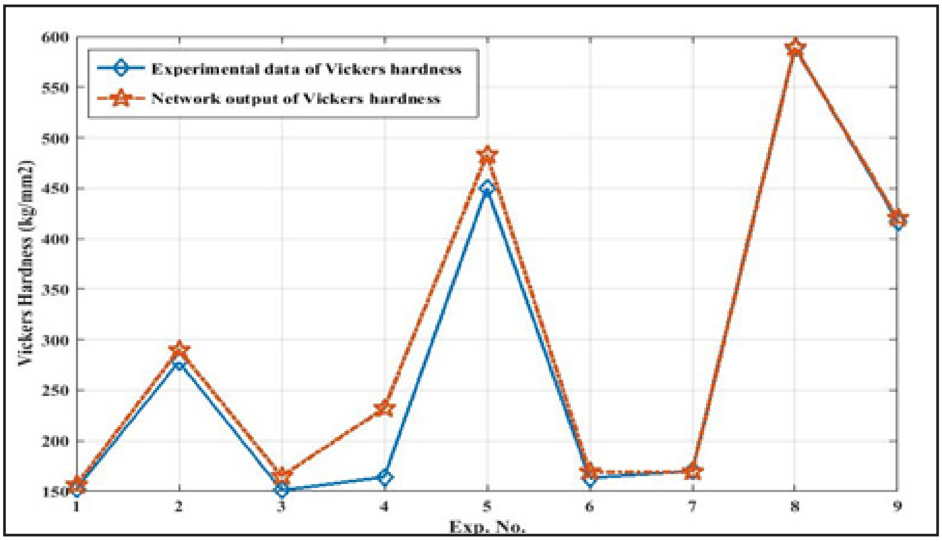


Figure 11.The artificial neural networks output vs. experimental no. for first model (A, B and C) respectively.

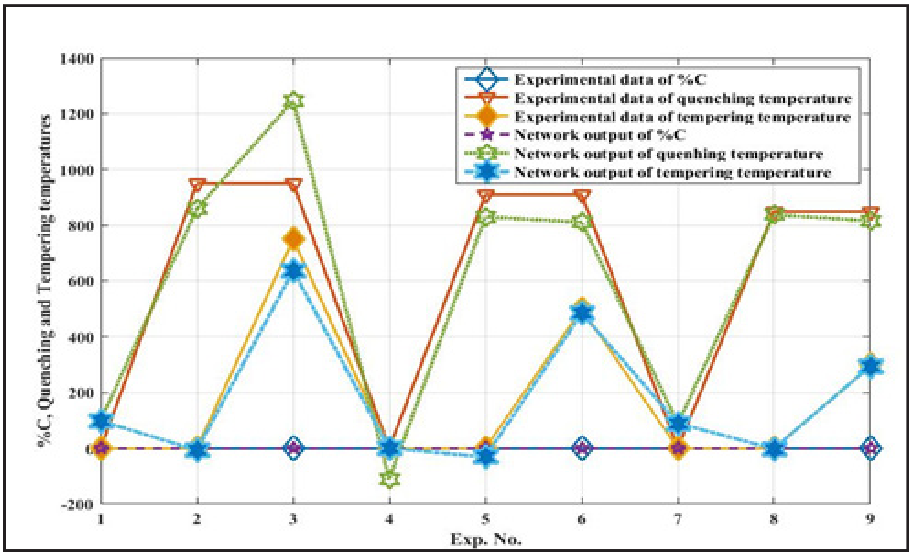


Figure 12. Comparison between experiment data and predict data of mechanical properties for second model.

5 Conclusion

Based upon this investigation findings, the conclusions made are

1- The strengthing procedures (by heat treatment and %C) and the artificial neural networks (ANNs) models afford powerful and reliable results

2- It can be used effectively to simulate the material properties such as hardness, yield strength and tensile strength problems of low and medium carbon steels

References

1- Adnan, Calik, Effect of cooling rate on hardness and microstructure of AISI 1020, AISI 1040 and AISI 1060 Steels; International journal of physical sciences 4-9(2009) 514-518.

2- Bila , M. Zahran, Using neural networks to predict the hardness of aluminum alloys; 5-1(2015)757-759.

3- Ceschini, L., M. Alessandro and M. Andrea, Correlation between ultimate tensile strength and solidication microstructure for the sand cast A357 Aluminum alloy; Mater Des 30-10(2009)4525-4531.

4- Degarmo, E. Paul, J T. Black and Ronald A. Kohser, Materials and processes in manufacturing (10th ed.); Wiley (2007).

5- E.Alibeiki, J. Rajabi, J. Rajabi, Prediction of mechanical properties of to heat treatment by artificial neural networks; Journal of Asian scientific research, 2(2012)742-746.

6- Elia E., Levi., Practical hardness testing made simple;(2003)1-21.

7-Fábio Ghignatti Beckenkamp., A componet artificial neural network systems;(2002)33-37.

8- Jeremy T. Busby, Mark C. Hash, Gary S. Was., The relationship between hardness and yield stress in irradiated austenitic and ferritic steels; Journal of nuclear materials, 336(2005)267–278.

9- Khorsand, H., et al., Application of artificial neural network for prediction of heat treated sintered steels properties; Trans tech. publications (ttp), 273-276(2008)323-328. <www.scientific.net>.

10- M. Gasko, G. Rosenberg., Correlation between hardness and tensile properties in ultra-high strength dual phase steels; Short communication materials engineering- materialove inzinierstvo, 18(2011)155-159.

11- Odusote, J. K., T. K. Ajiboye and A. B. Rabiu., Evaluation of mechanical properties of medium carbon steel quenched in water and oil; Journal of minerals and materials characterization and engineering, 11(2012)859-862.

12- Partheepan, G., D. K. Sehgal and R. K. Pandey., Quasi - non - destructive evaluation of yield strength using neural networks; Hindawi publishing corporation advances in artificial neural systems, 20-11(2011)8.

13- R. A. Grange, C. R. Hribal, and L. F. Porter, Hardness of tempered martensite in carbon and low alloy steels, 8A(1977).

14- V.K.Murugan, Dr.P.Koshy Mathews, Effect of tempering behavior on heat treated medium carbon (C 35 Mn 75) steel; International journal of innovative research in science; Engineering and technology, 2-4(2013)945-950.

15-Woei-Shyan Lee, Tzay-Tian Su, Mechanical properties and microstructural features of AISI 4340 high-strength alloy steel under quenched and tempered conditions; Journal of materials processing technology, 87(1999)198–206.