International Journal of Modern Manufacturing Technologies
ISSN 2067–3604, Vol. V, No. 2 / 2013

NEURAL NETWORKS TO PREDICT MICROHARDNESS OF NAVAL STEEL BY CHEMICAL COMPOSITION

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Abstract: In this paper, the MATLAB with Artificial Neural Networks toolbox is used for artificial neural networks was developed to predict microhardness of shipbuilding steel plate A36. Different modeling method based on artificial neural networks is used by many researchers for a wide range of engineering applications. Different researchers propose some models to predict microhardness using neural networks, but these models need to be extended. We propose a model with two hidden layers feed forward type of artificial neural networks for predict microhardness. In our study we consider the carbon equivalent, based upon the International Institute of Welding equation and the carbon equivalent equation related to Ito-Bessyo considering the chemical composition based on nickel, silicium, manganum, copper, niobium, vanadium, titanium, chromium molybdenum, and the Charpy impact energy. As input we consider the chemical composition of different naval high resistance steel plates. We consider more than 50 different data were gathered from experimental results. We consider different format of input parameters that cover the chemical composition and Charpy impact energy and output parameter which is microhardness. The networks was trained to predict the microhardness amounts as output.The artificial neural networs was developed and training using a back propagation algorithm applied to the experimental data from literature. In our study, the back propagation training algorithm has been used in feed forward for hidden layers of our artificial neural networks architecture. Back propagation algorithm, is one of the most used training algorithms for the multilayer perceptron, is a gradient descent technique to minimize the error for particular training pattern in which it adjust the weights. The assignment of initial weights and other related parameters may also influence the performance of the artificial neural network. We consider two different models for neural networks architecture, and the performance of them will be tested. All of the results obtained from experimental studies and predicted by using the training, testing and validation results for two different neural networks architecture will be given. We optimized the neural network architecture to find the best equation to predict microhardness values by specific inputs. The predicted values are in very good agreement with the measured ones.

Key words: Artificial network, Microhardness, A36 steel plate.

1.INTRODUCTION

Modern commercial ship designs in the last years have shown a continuing trend of increased utilization of high strength, alloy steel plate for weight reduction, increased payload, and increased mobility. The loads that affect the ship's structure, have special mentions regarding to the structural strength limitations imposed by the ship's classification society. The ship structures are subjected to a complex range of dynamic loadings in service and stresses built into the hull during fabrication. The dynamic loads include wave loadings, sea slap, slamming, vibration, thermal excursions (Hawthorne, 1975).

The principal factors contributing to the loss of the ships were corrosion and cracking of the structure. Also others factors which could have contributed to the hull structural failure were over-stressing of the hull structure due incorrect loading and physical damage to the side structure during various operations.

The fracture safety assurance of the ship's hull has assumed increased importance from each type of destination ship. In the world commercial shipbuilding steels have been classified by the various bureau of shipping according to chemistry, strength level, and heat treatment (Hawthorne, 1981).

The steel grades for ordinary-strength hull applications are from American Bureau Shiping (ABS) classification steels in Grade A, B, C, D and E and for American Society for Testing and Materials (ASTM) ASTM A36, ASTM A514. Test materials (plate) were obtained at random from several shipyards in an effort to characterize the products of current steel making practice.

The proportion of Grade A ship plate, a grade with no toughness requirement in large ships is 80-85% and up to 95% in small and intermediate sized vessels. The remaining material is usualy grade B, D and AH32/36 or DH32/36 for higher stressed areas (Health, 1997).

Table 1. Minimum Charpy levels for steel ships

Rules	Grade									
	A	B (at 0°C)	D (at 10°C)	E (at -40°C)	AH32 (at 0°C)	DH32 (at -20°C)	EH32 (at -40°C)	AH36 (at 0°C)	DH36 (at -20°C)	EH36 (at -40°C)
ABS	-	27	27	27	34	34	34	34	34	34
DNV	-		27	27	31	31	31	34	34	34
Lloyds	-	27	27	27	31	31	31	34	34	34

The International Association of Classification Societies (IACS) classification rules assume the minimum Charpy levels for Grades B, C and D to be 27 J at 0°C, -10°C and -40°C respectively. Grade A has no requirements but 27 J at 10°C is often assumed (IACS, 2008) is given in Table 1.

In steel-related research, which is also the focus of this study, ANN has been used widely to understand a wide range of problems including mechanical properties (Nazari, 2011), (Nazari et al., 2011), toughness of welding alloys (Metzbower et al., 2001), metal deformation (Lightfoot et al., 2005), surface texture (Tugrul and Yigit, 2005), (Fredj and Amamou 2006) and phase transformations (Khalaj et al., 2012). Also we can applyed ANN to decide the composition of steel for achieving a particular hardness (Trzaska and Dobrzanski, 2005).

The identification of properties of unknown material in the material testing laboratory requires heavy investment and also it is very time consuming. The use of simulation software in conducting experiments and prediction of properties of material will reduce the cost. The application of neural network modeling for evaluation of the effect of the alloying elements in predicted UTS and microhardness on naval steels is presented.

The developed ANN-1 and ANN-2 models can also be employed for simulations of the relationship between mechanical property and the chemical composition of naval steel. This can be done in the entire range of concentrations of the main alloying elements occurring in naval steels taken as data set. Applications of the presented method enables a scientist to make free analyses of the effect of the alloying elements occurring in processing condition also using only computer simulation, without having to carry out additional and expensive experimental investigations.

In this research, ANNs has been employed to determine ultimate tensile strength and the microhardness. ANN has been used to determine the ultimate tensile strength as a function of fourteen alloying elements (C, Si, Mn, P, S, Al, Ti, V, Cu, Ni, Cr, Mo, Nb, and N_2). The theory behind the ANN configuration and the performance with regard to high-strength low-carbon steels is discussed in the next sections. More precisely, using the experimental data of 63 naval steels, the ANN-1 has been developed to predict the ultimate tensile strength and the ANN-2 has been developed to predict microhardness for a given set of input variables mentioned above.

2. ARTIFICIAL NEURAL NETWORK THEORY

Neural networks find their origin in biological science. However, the basis of that has been extended to artificial neural networks, which is the general terminology used to describe the mathematical models.

McCulloch and Pitts (McCulloch and Pitts, 1943) defined artificial neurons for the first time and developed a neuron model. In 1958 Frank Rosenblatt, an American psychologist, proposed the perceptron, a more general computational model than McCulloch–Pitts units (Rojas, 1996). The essential innovation was the introduction of numerical weights and a special interconnection pattern. In the original Rosenblatt model the computing units are threshold elements and the connectivity is determined stochastically. Learning takes place by adapting the weights of the network with a numerical algorithm. Rosenblatt's model was refined and perfected in the 1960s and its computational properties were carefully analyzed by Minsky and Papert (Minsky and Papert, 1969). McCulloch and Pitts' network formed the basis for almost all later neural network models, as in Figure 1.

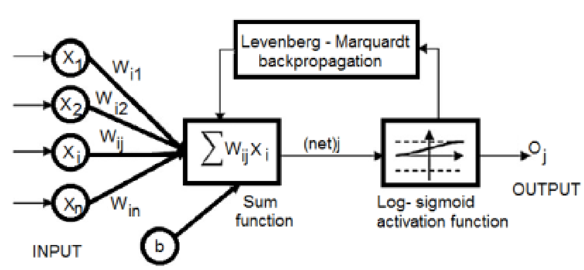

Fig. 1 Architecture of neural network, [Ince, 2004]

Their adaptive nature is a very important feature of these networks, where "learning by example" replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available (Somkuwar, 2012).

The basis of a neural network is shown in figure 1 is composed of five main parts: the inputs x_i in the first layer of neurons, weights W_{ij} accepted by each neuron, sum function, activation function (purelin function, log-sigmoid or tangential function) and the outputs O_j.

Inputs are information that enters the neuron from other neurons of from external world. Weights are values that express the outcome of an input set or another process element in the preceding layer on this process element.

Sum function is a function that calculates the effect of inputs and weights completely on this process element. This function computes the net input that approaches a neuron (Beale et al., 2013). The weighted sums of the input components (net)j are calculated using the below equation as follows:

$$(net)_j=\sum W_{ij}x_i+b \quad (1)$$

where $(net)_j$ is the weighted sum of the jth neuron for the input received fromthe preceding layer with n neurons, W_{ij} are the interconnections weights between the j-th neuron in the previous layer, x_i is the output of the ith neuron in the previous layer (Beale et al., 2013), b represent the bias for the neuron and have a fix value as internal addition. Activation function is a function that processes the net input obtained from sum function and determines the neuron output. In general for multilayer feed-forward models as the activation function, sigmoid activation function is used. The output of the jth neuron $(out)_j$ is computed using Eq. (1) with a sigmoid activation function as follows (Hopfield, 1982).

$$O_j=f(net)_j=1/(1+e^{-\alpha(net)_j}) \quad (2)$$

where α is constant used to control the slope of the semilinear region. The sigmoid nonlinearity activates in every layer except in the input layer (Beale et al., 2013). The sigmoid activation function represented by Eq. (2) gives outputs in (0, 1).

Neural networks consist of a large class of different architectures. The most useful neural networks in function approximation are Multilayer Layer Perceptron (MLP) and Radial Basis Function (RBF) networks.

A typical architecture of a multilayer perceptron neural network is composed of the following components:

- one input layer that receives signal from the environment;
- one or more outputs layer that conveys the signals to the environment;
- one or more hidden layers that keep some input and output signals within the network itself.

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Figure 2 shows a typical architecture of a multilayer perceptron neural network with an input layer, two hidden layers and one output layer.

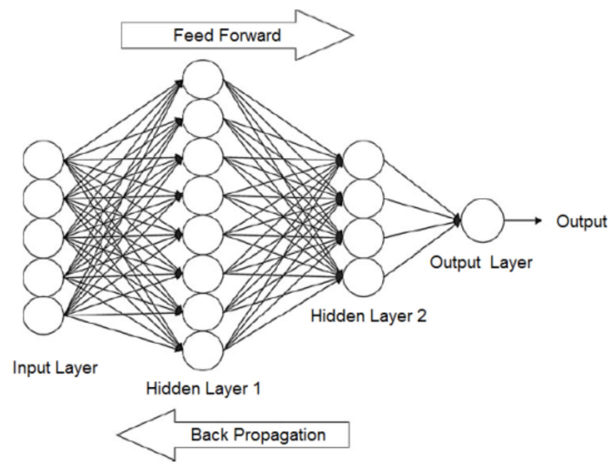


Fig. 2 The architecture of multilayer percepton neural network, [Nazari, 2012]

Many algorithms exist for determining the network parameters. In neural network literature the algorithms are called *learning* or *teaching* algorithms, in system identification they belong to *parameter estimation* algorithms. The most well-known are back-propagation and Levenberg-Marquardt algorithms. Backpropagation algorithm, one of the most well-known training algorithms for the multilayer perceptron, is a gradient descent technique to minimize the error for a particular training pattern in which it adjusts the weights by a small amount at a time (Rojas, 1996). For small- and medium-sized networks and patterns, the Levenberg–Marquardt algorithm is remarkably efficient and strongly recommended for neural network training (Yu and Wilamowski, 2011).

The procedure of teaching algorithms for multilayer perceptron networks consist in:

a. Defined the structure of the network. In the network, it is necessarily to choose activation functions and to initialize weights and biases.
b. We define the parameters associated with the training algorithm like error goal, maximum number of epochs.
c. Call the training algorithm.
d. At the end when the neural network has been determined, the result is first tested by simulating the output of the neural network with the measured input data. This is compared with the measured outputs. Final validation must be carried out with independent data.

3. DATA COLLECTION

The study of naval steels is important because naval steels represent by far the most widely used materials by shipbuilders, and can be manufactured relatively cheaply in large quantities to precise specifications. In our study naval steel is selected as the reference group for developing a database for material identification and prediction of property using its chemical composition.
In the present investigation, the artificial neural network has been trained, tested and validated for prediction microhardness and ultimate tensile for naval steel using in shipbuilders.
For this purpose, the experimental data from Constantza shipbuilder of A36, ASTM 514 (Higashida et al., 1978), A710 (Trzaska and Dobrzanski, 2005), Grade B (Health and Safety Executive, 1997), Grade D (Lightfoot et al., 2005) and Grade E (Jesseman and Schmid, 1979) steels with different chemical compositions have been used. The input variables of the ANN modeling are the weight percent of alloying elements, carbon equivalent. These parameters along with their range have been summarized in Table 2.

Table 2. The range of the input and the output parameters in ANN model

Parameters	Minimum	Maximimum	Mean	Standard deviation
Input				
C (wt%)	0.05	0.27	0.166508	0.043558
Si (wt%)	0.008	0.4	0.208857	0.131653
Mn (wt%)	0.42	1.58	1.112619	0.400342
P (wt%)	0	0.12	0.012683	0.016905
S (wt%)	0	0.025	0.006492	0.00671
Al (wt%)	0	0.053	0.026079	0.021267
Ti (wt%)	0	0.1	0.00681	0.016375
V (wt%)	0	0.042	0.002381	0.006124
Cu (wt%)	0	1.3	0.084968	0.277384
Ni (wt%)	0	0.9	0.066508	0.195012
Cr (wt%)	0	0.51	0.022603	0.065089
Mo (wt%)	0	0.2	0.011302	0.028747
Nb (wt%)	0	0.06	0.009032	0.016282
N (wt%)	0	0.009	0.003189	0.00374
Output				
UTS [MPa]	368	938	502.381	84.63421

4. ANN MODEL CONSTRUCTION

Two ANN modeled in this research. The input layers has fourteen neurons for every ANN and the parameters are given in Table 3 and 4.

Table 3. The Neural Networks values used in ANN model 1

Parameters	ANN
Number of input layer units	14
Number of hiden layers	2
Number of first hidden layer units	12
Number of second hidden layer units	9
Number of output layer units	1

The values for input layers were carbon weight percent (C), silicon weight percent (Si), manganese weight percent (Mn), phosphorous weight percent (P), sulfur weight percent (S), aluminum weight percent (Al), titanium weight percent (Ti), vanadium weight percent (V), copper weight percent (Cu), nickel weight percent (Ni), chromium weight percent (Cr), molybdenum weight percent (Mo), niobium weight percent (Nb), nitrogen weight percent (N) and the carbon equivalent weight (C_{eq}), based upon the International Institute of Welding equation (Eq. 3).

Table 4. The Neural Networks values used in ANN model 2

Parameters	ANN
Number of input layer units	14
Number of hiden layers	2
Number of first hidden layer units	7
Number of second hidden layer units	5
Number of output layer units	1

Also we compute the carbon equivalent, based upon the chemical portion of the Ito-Bessyo carbon equivalent equation (P_{cm}) (Eq. 4).
The carbon equivalent C_{eq} as determined from the ladle analysis in accordance with the following equation:

$$C_{eq}=C+Mn/6+(Cr+Mo+V)/5+(Ni+Cu)/15 \qquad (3)$$

The cold cracking susceptibility P_{cm} as calculated from the ladle analysis in accordance with the following equation is:

$$P_{cm}=C+Si/30+(Mn+Cu+Cr)/20+Ni/60+Mo/15+V/10+5 \quad (4)$$

The neurons of neighboring layers are completely interconnected by weights.
Finally, the output layer neurons produce the network prediction as a result.
From the total 63 gathered date, 40 were randomly selected and trained by the network, 23 data were used for validation and the other 23 data were used for testing the network. In this study, the back-propagation training algorithm has been utilized in one feed-forward hidden layer.
The nonlinear sigmoid activation function was used in each the hidden layer and purelin in the neuron outputs at the output layer. The trained model was only tested with the input values, and the predicted results were close to experiment results.

5. RESULTS AND DISCUSSION

5.1 The effects of chemical composition

The parameter that has been most used in practice to measure steel weldability is the carbon equivalent (C_{eq}) equation (3), where good weldability is in general obtained by maintaining a low C_{eq} .

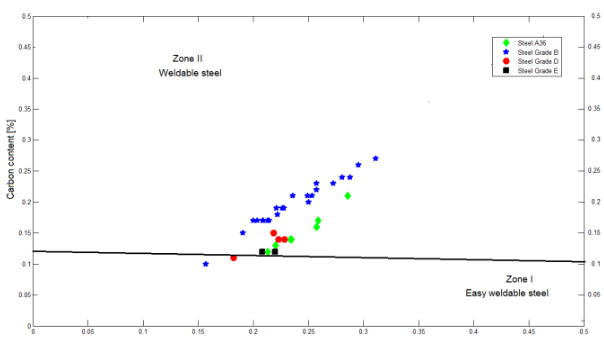


Fig. 3 The variation of chemical compositions carbon content, carbon equivalent and weldability diagram for naval steels

From the Figure 3 we conclude that all naval steels that we studied are good weldability.

5.2. ANN Modeling with MATLAB

Back-propagation multilayer feedforward ANNs (ANN-1 and ANN-2) were created using the Neural Network Toolbox in Matlab 7 package. ANN-1 comprise the input layer, two hidden layer and the output layer, see Figure 4.

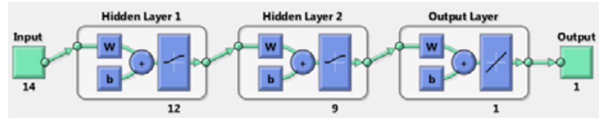


Fig. 4 The ANN-1 model used in MATLAB

Also ANN-2 comprise the input layer, two hidden layer and the output layer, see Figure5.

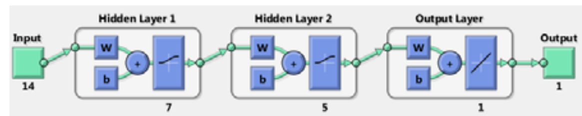
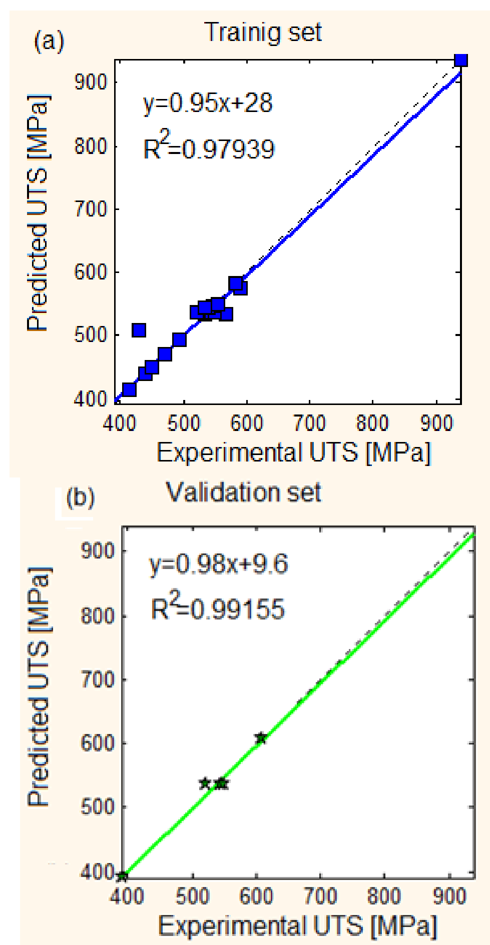


Fig. 5 The ANN-2 model used in MATLAB

5.3 Training and Validation

The ANNs are trained by introducing a set of examples of proper network behaviour to the ANNs. During training, the learning rule is used to iteratively adjust the weights and biases of the network in order to move the network outputs closer to the target values by minimizing the network performance indicator.
The Levenberg-Marquardt training algorithm, which has a higher rate of convergence, is used for the training of both ANN-1 and ANN-2.



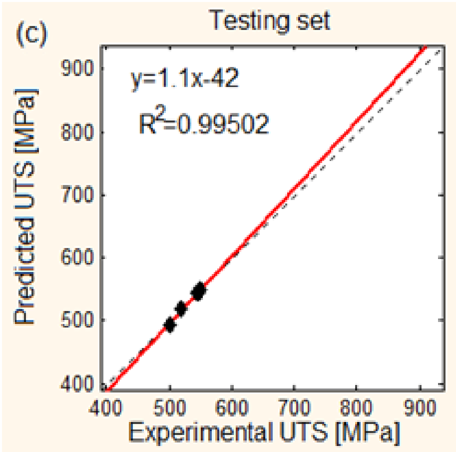


Fig. 6. Correlation of the measured and predicted ultimate tensile strength values in (a) training, (b) validation, (c) testing sets for ANN model 1

Figure 6 presents the comparison between measured and predicted results for ultimate tensile strength levels for naval steels. We consider that this approach can be very useful in modeling the mechanical properties of naval steels, because there is a concordance between the predicted and measured values indicated. The prediction values match the measured amounts very well. This clearly indicates the accurate function of the trained ANN-1 in predicting the ultimate tensile strength of naval steels. In Figure 6a, b and c, we present the training, validation and testing predicted UTS results of ANN-1 model, and these results are obtained from experimental studies. The linear least-square fit line, its equation and the R^2 values are shown also in these figures for the training, validation and testing data. It can see in Figure 6, the values obtained from the training, validation and testing in ANN-1 model are very close to the experimental UTS data results. Also the result of testing phase in Figure 6 shows that the ANN-1 model are capable of generalizing between input and output variables with reasonably good predictions. The best value of R^2 is 99.5 % for testing set in the ANN-1 model. All of R^2 values show that the proposed ANN-1 model are suitable and can predict UTS values very close to the experimental values. Knowing the relationship between ultimate tensile strength (UTS) and hardness HV (Pavlina, 2008) given by equation:

$$UTS=3.3*HV \qquad (5)$$

and from all data of the specimens we have the experimental values of UTS and we compute, from equation (5), the microhardness values.

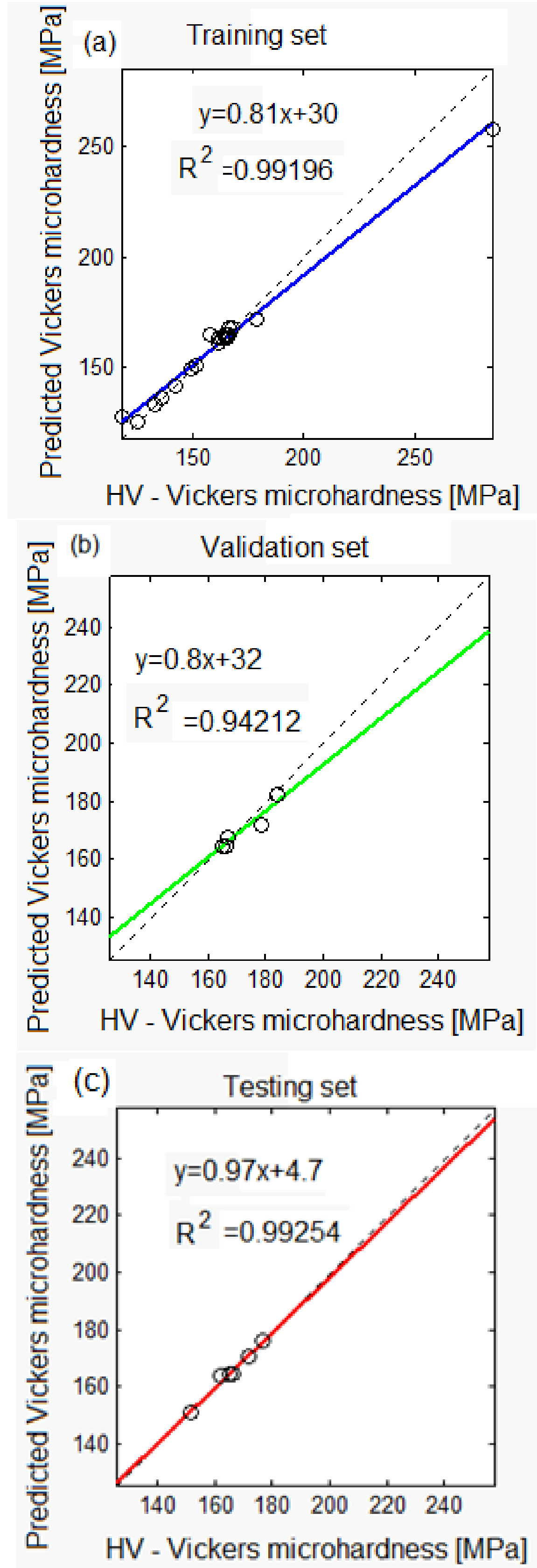


Fig. 7. Correlation of the measured and predicted HV microhardness values in (a) training, (b) validation and (c) testing sets for ANN model 2

In Figure 7 a, b and c, we present the training, validation and testing predicted HV microhardness results of ANN-2 model.
The linear least-square fit line, its equation and the R^2 values are shown also in these figures for the training, validation and testing data.
It can see in Figure 7, the values obtained from the training, validation and testing in ANN-2 model are very close to the computed microhardness HV data results. Also the result of testing phase in Figure 7 shows that the ANN-2 model are capable of generalizing between input and output variables with reasonably good predictions. The best value of R^2 is 99.25 % for testing set in the ANN-2 model.
All of R^2 values show that the proposed ANN-2 model are suitable and can predict microhardness values very close to the computed values.

6. CONCLUSIONS

Two artificial neural network models (ANN-1 and ANN-2) were developed to predict the ultimate tensile strength and microhardness of naval steels. The values predicted in the presented models are in very good agreement with those measured by experimental results, and computed respectivelly. Therefore, the presented ANN models can be used to predict accurately the ultimate tensile strength of naval steels and microhardness also. ANN models will be valid within the ranges of variables.

Note

"This paper was presented at the ModTech2013 International Conference -Modern Technologies in Industrial Engineering, held between June 27-29, 2013 in Sinaia, Romania".

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Received: June 01, 2013 / Accepted: December 5, 2013 / Paper available online: December 10, 2013 © International Journal of Modern Manufacturing Technologies.